Has the Financial Crisis Changed the Business Cycle Characteristics of the PIIGS Countries?

By

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and

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Abstract: Since the financial crisis erupted in 2008, the governments of Portugal, Ireland, Italy Greece and Spain (PIIGS) find themselves in a position where financing their debts becomes increasingly difficult. As a result, these governments reduced government expenditure and/or increased taxes in order to reduce their deficits. Hence, whilst other countries in the Eurozone – notably Germany - enjoy a recovery from the financial crisis, the PIIGS countries remain in recession. It is therefore no surprise that the business cycles of the northern and southern European countries diverge increasingly. This in itself poses already a risk for the Eurozone, as it makes the common monetary policy less effective.

However, in this paper we analyse the business cycles in greater detail. We ask whether the financial crisis has changed the characteristics of the business cycles of the PIIGS countries. For example, the introduced austerity measures in Greece may well lead to a convergence ofgovernment speding between Germany and Greece and therefore to a greater convergence of the business cycles of both countries, despite the fact that currently both countries are on different cycles. If this development is the case, then at least there is some hope that in future the common monetary policy will be more effective. But the austerity measures could also lead to a greater divergence between Greece and Germany, in which case leaving the monetary Union would not only be benefitial for Greece, but also unavoidable.

Keywords: Time-Frequency Analysis, Coherence, Growth Rates, Business Cycle

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1 Introduction

Although, this paper is asking and analysing whether the financial crisis has changed the business cycle characteristics of the PIIGS countries (Portugal, Ireland, Italy, Greece and Spain); it is also investigating what effect the financial crisis had on those countries with respect to the convergence of business cycles in the Eurozone. If the business cycle charactersitics of one Eurozone country changes then that has consequences for the other Eurozone countries as well unless all countries' business cycle characteristics change in the same way.

The financial crisis and associated with it, the new fiscal policies could theoretically lead to a greater convergence of business cylces as the PIIGS countries behave more like their nordic neighbours or they could drift further away, because the austerity measures which are only taken in those countries lead to a further diversification of the business cycles.

This is a very difficult area to investigate, because there is no consensus that business cycles have converged prior to the financial crisis. So to what extent are different countries' growth cycles becoming more correlated across Europe in particular? Is there evidence of cyclical convergence at the business cycle frequency (the focus for policy purposes), or at any other frequencies in the Euro area? Does that imply a common European cycle? Cyclical convergence is an essential condition for the success of a single currency (the Eurozone), or the assumption of a currency and associated monetary policies from abroad (dollarisation).

As mentioned above, a selective reading of the literature could lead to almost any conclusion. We therefore add a third question: how should we go about measuring cyclical convergence in this context? In this paper we show how spectral analysis can be used to answer these questions, even where data samples are small, and where structural breaks and changing structures are an important part of the story. We need a spectral approach to determine the degree of convergence at different frequencies or cycles. The inconclusive results obtained in the past may have been the result of using a correlation analysis which averages the degree of convergence across all frequencies. Two economies may share a trend or short terms shocks, but show no coherence between their business cycles for example.

These questions are not easy to answer. From a theoretical perspective, neoclassical growth models show that every economy approaches a steady-state income level determined by the discount rate, the elasticity of factor substitution, the depreciation rate, capital share, and population growth. Once at the steady-state, the economy grows at a constant rate. Thus, to the extent that the determinants of the steady-state are similar across economies, convergence is expected. But if these determinants are different, they will not converge. Thus, Mankiw et al. (1992), Dowrick and Nguyen (1989), Wolff (1991), Barro and Sala-I-Martin (1991; 1992), Quah (1993) find evidence of convergence for a sample of OECD countries at similar levels of development over the years 1960-1985. But they reject that convergence hypothesis in a wider sample of 75 economies whose structures and degree of uncertainty vary a good deal more. Similarly, Chauvet and Potter (2001) report that the US business cycle was in line with the G7 from the mid 70s, but then diverged thereafter. Likewise Stock and Watson (2002; 2003), Hughes Hallett and Richter (2006) find divergence caused by structural breaks, and argue that cyclical convergence is a global rather than regional phenomenon.

As far as the Eurozone is concerned, Artis and Zhang (1997) and Frankel and Rose (1998) have argued that if exchange rates are successfully pegged, and trade and financial links intensify, business cycles are likely to converge. On the other hand, Inklaar and de Haan (2000) do not find any evidence for a European business cycle in practice. Similarly, Gerlach (1989) and Baxter and Kouparitsas (2005) find no evidence of greater convergence among the OECD economies as exchange rates stabilise or trade increases.(see also: Doyle and Faust, 2003; Kalemli-Ozcan et al., 2001; Peersman and Smets, 2005) provide further evidence in the same direction. All these results suggest a time-varying approach is going to be necessary if we are to analyse an emerging convergence among economies[1].

The studies cited above also make it clear that the results in this literature are sensitive to: a) the choice of coherence measure (correlation, concordance index); b) the choice of cyclical measure (classical, deviation or growth cycles); and c) the detrending measure used (linear, Hodrick-Prescott filter, band pass etc.). This sensitivity to the detrending technique is a problem highlighted in particular by Canova (1998). The advantages of using a time-frequency approach are therefore:

i) It does not depend on any particular detrending technique, so we are free of the lack of robustness found in many recent studies.

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[1] Also because structural characteristics and institutions change. It appears that cyclical correlations typically fall with the degree of industrial specialisation which increases, both in Europe and beyond, as trade and financial

ii) Our methods also do not have an “end-point problem” – no future information is used, implied or required as in band-pass or trend projection methods.

iii) There is no arbitrary selection of a smoothing parameter, such as in the HP algorithm, equivalent to an arbitrary band-pass selection (Artis et al., 2004).

iv) We use a coherence measure which provides more detailed information than the conventional correlation and concordance measures.

However, any spectral approach is tied to a model based on a weighted sum of sine and cosine functions. That is not restrictive. Any periodic function may be approximated arbitrarily well over its entire range, and not just around a particular point, by its Fourier expansion (a suitably weighted sum of sine and cosine terms) – and that includes non-differentiable functions, discontinuities and step functions. Hence, once we have time-varying weights, we can get almost any cyclical shape we want. For example, to get long expansions, but short recessions, we need only a regular business cycle plus a longer cycle whose weight increases above trend but decreases below trend (i.e. varies with the level of activity). This is important because many observers have commented on how the shape of economic cycles has changed over time in terms of amplitude, duration and slope (Harding and Pagan, 2001; Peersman and Smets, 2005; Stock and Watson, 2002). Once again, a time-varying spectral approach is necessary to provide the flexibility to capture these features. Similarly it is needed if we are to accommodate, and reveal, the possibility of structural breaks which must be expected with the breakdown of the EMS, the coming of the Euro, the changes in monetary institutions, and the increasing integration and volatility of financial markets.

2 A Technical Introduction to Time Frequency Analysis

2.1 *Time Varying Spectra*

Spectral analysis decomposes the variance of a sample of data across different frequencies. The power spectrum itself then shows the relative importance of the different cycles in creating movements in that data, and hence describes the cyclical properties of a particular time series. It is assumed that the fluctuations of the underlying data are produced

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integration intensify (Kalemli-Ozcan et al 2001, 2003).Then there are induced market reforms, liberalisation measures, and the extent to which policies are coordinated or made common to a group of economies.

by a large number of elementary cycles of different frequencies. Furthermore, it is usually assumed that the contribution of each cycle is constant throughout the sample. However, as Chauvet and Potter (2001) show for the US, business cycles cannot be assumed to be constant. Hence, the spectrum would not be constant over time due to the changing weights associated with each of the elementary cycles. A "traditional" frequency analysis cannot handle that case. But in recent years a time frequency approach has been developed which can do so. It depends on using a Wigner-Ville distribution for the weights (see for example: Matz and Hlawatsch, 2003). In this paper we use a special case of the Wigner-Ville distribution, namely the "short time Fourier transform" (STFT). The STFT catches structural changes (here interpreted as changes of the underlying lag structure in accordance with Wells, 1996), but assumes local stationarity. We employ the STFT for two reasons: first, the time series we analyse are already in log-differenced form (see eq. (2.1) below) so stationarity may be assumed. Moreover, standard unit root tests performed on our data (specifically ADF and the Phillips-Perron tests, available on request) confirm that assumption. Finally, the available results in the literature on similar data (Campbell and Mankiw, 1987; Clark, 1987; Todd, 2003; Watson, 1986) also confirm that conclusion. Secondly, if the time series is stationary, then the STFT and the Wigner-Ville distribution actually coincide (Boashash, 2003). Therefore, employing the Wigner-Ville distribution directly would not have changed our results.

All the data collected (including the Eurozone data) are real GDP from the OECD main indicators. We use seasonally adjusted quarterly data from 1980:1 to 2005:1. For countries inside the Euro area and the Eurozone itself, GDP is expressed in Euros over the entire sample. Growth rates are then defined, using GDP data, as follows:

$$y_t = \Delta\left(\log\left(Y_t\right)\right) = \log\left(\frac{Y_t}{Y_{t-1}}\right) \tag{2.1}$$

Next we employ a two step procedure. As Evans and Karras (1996) point out, if business cycles are to converge, they have to follow the same AR(p) process. We therefore estimate an AR(p) process for each variable individually. That is, we estimate the data generating process of each of the growth rates separately. Then we estimate the bilateral links between the cycles in those growth rates. In order to allow for the possible changes in the parameters, we employ a time-varying model by applying a Kalman filter to the chosen AR(p) model as follows:

$$y_t = \alpha_{0,t} + \sum_{i=1}^{9} \alpha_{i,t} y_{t-i} + \varepsilon_t \tag{2.2}$$

with $$\alpha_{i,t} = \alpha_{i,t-1} + \eta_{i,t},\ \text{for i=0...9} \tag{2.3}$$

and $\varepsilon_t, \eta_{i,t} \sim \text{i.i.d.}\left(0, \sigma^2_{\varepsilon,\eta_i}\right)$, for i=0...9.

In order to run the Kalman filter we need initial parameter values. The initial parameter values are obtained estimating them by OLS using the entire sample (see also Wells, 1996)[2]. Given these starting values, we can then estimate the parameter values using the Kalman filter. We then employed a general to specific approach, eliminating insignificant lags using the strategy specified below. The maximum number of lags was determined by the Akaike Criterion (AIC), and was found to be nine in each case. Each time we ran a new regression we used a new set of initial parameter values. Then, for each regression we applied a set of diagnostic tests shown in the tables in Appendix 1, to confirm the specification found. The final parameter values are filtered estimates, independent of their start values.

Using the above specification implies that we get parameter values for each point in time. Hence, a particular parameter could be significant for all points in time; or at some but not others; or it might never be significant. The parameter changes are at the heart of this paper as they imply a change of the lag structure and a change in the spectral results. We therefore employed the following testing strategy: if a particular lag was never significant then this lag was dropped from the equation and the model was estimated again. If the AIC criterion was less than before, then that lag was completely excluded. If a parameter was significant for some periods but not others, it was kept in the equation with a parameter value of zero for those periods in which it was insignificant. This strategy minimised the AIC criterion, and leads to a parsimonious specification. Finally, we tested the residuals in each regression for auto-correlation and heteroscedasticity.

The specification (2.2) – (2.3) was then *validated* using two different stability tests. Both tests check for the same null hypothesis (in our case a stable AR(9) specification)

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[2] Obviously, using the entire sample implies that we neglect possible structural breaks. The initial estimates may be biased therefore. The Kalman filter will then correct for this since, as Wells (1996) points out, the Kalman filter will converge to the true parameter value independently of the initial value. But choosing initial values

against differing temporal instabilities. The first is the fluctuations test of Ploberger et al. (1989), which detects *discrete* breaks at any point in time in the coefficients of a (possibly dynamic) regression. The second test is due to LaMotte and McWorther (1978), and is designed specifically to detect *random* parameter variation of a specific unit root form (our specification). We found that the random walk hypothesis for the parameters was justified for each country (results available on request). Finally, we chose the fluctuations test for detecting structural breaks because the Kalman filter allows structural breaks at any point and the fluctuations test is able to accommodate this.[3] Thus, and in contrast to other tests, the fluctuations test is not restricted to any pre-specified number of breaks.[4]

Once this regression is done, it gives us a time-varying AR(p) model. From this AR(p) we can *calculate* the short–time Fourier transform (STFT), as originally proposed by Gabor (1946), in order to calculate the time-varying spectrum. The basic idea is to find the spectrum of a signal x(t), at time t, by analysing a small portion of the signal around that time.

a) Spectra: Boashash and Reilly (1992) show that the STFT can always be expressed as a time-varying discrete fast-Fourier transform calculated for each point in time. That has the convenient property that the "traditional" formulae for the coherence or the gain are still valid, but have to be recalculated at each point in time. The time -varying spectrum of the growth rate series can therefore be calculated as (see also: Lin, 1997):

$$P_t(\omega) = \frac{\sigma^2}{\left|1 + \sum_{i=1}^{9} \alpha_{i,t} \exp(-j\omega i)\right|_t^2} \tag{2.6}$$

where ω is angular frequency and j is a complex number. The main advantage of this method is that, at any point in time, a power spectrum can be calculated instantaneously from the

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which are already "close" to the true value accelerates convergence. Hence we employ an OLS estimate to start. But our start values have no effect on the parameter estimates by the time we get to 1990. Our results are robust.

[3] Note that all our tests of significance, and significant differences in parameters, are being conducted in the time domain, *before* transferring to the frequency domain, because no statistical tests exist for calculated spectra (the transformations may be nonlinear and involve complex arithmetic). Stability tests are important here because our spectra could be sensitive to changes in the underlying parameters. But with the stability and specification tests conducted, we know there is no reason to switch to another model that fails to pass those tests.

[4] The fluctuations test works as follows: one parameter value is taken as the reference value, e.g. the last value of the sample. All other observations are now tested whether they significantly differ from that value. In order to do so, Ploberger et al. (1989) have provided critical values which we have used in the figures (horizontal line). If the test value is above the critical value then we have a structural break, i.e. the parameter value differs significantly from the reference value and vice versa.

updated parameters of the model (see also Lin, 1997). Similarly, the power spectrum for any particular time interval can be calculated by averaging the filter parameters over that interval. This would then result in the "traditional" spectra.

b) Cross-spectra: Returning to the second step of our analysis, we can now estimate the one to one relationship between two economies. We restrict ourselves to bilateral relationships in order to avoid multicollinearity between a series of potentially interrelated cycles.

By transferring the time domain results into the frequency domain, we can show how the relationship between two economies has changed in terms of individual frequencies. That is, we are able to investigate whether any convergence took place over time; and, if so, at which frequencies. As a measure of that relationship, we use the coherence. We then decompose the coherence in order to see whether a change in the coherence is caused by a change in the relationship between the two variables (i.e. in the ADL model below); or by a change in the data generating process itself (i.e. in the AR(p) model itself). With a time-invariant method that cannot be done. The next section outlines these ideas.

2.2 *Time Varying Cross-Spectra*

Suppose we are interested in the relationship between two variables, $\{y_t\}$ and $\{x_t\}$ say, where $\{y_t\}$ is the US growth rate and $\{x_t\}$ is a European growth rate. We assume that they are related in the following way:

$$V(L)_t\, y_t = A(L)_t\, x_t + u_t,\ u_t \sim \text{i.i.d.}\left(0, \sigma^2\right) \tag{2.7}$$

where A(L) and V(L) are filters, and L is the lag operator such that $Ly_t = y_{t-1}$. Notice that the lag structure, A(L), is time-varying. That means we need to use a state space model (we use the Kalman filter) to estimate the implied lag structure. That is

$$\begin{aligned} v_{i,t} &= v_{i,t-1} + \varepsilon_{i,t},\ \text{for i = 1, ..., p and } \varepsilon_{i,t} \sim \left(0, \sigma^2_{\varepsilon_i}\right) \\ a_{i,t} &= a_{i,t-1} + \eta_{i,t},\ \text{for i = 0, ..., q and } \eta_{i,t} \sim \left(0, \sigma^2_{\eta_i}\right) \end{aligned} \tag{2.8}$$

As before, we tested for the random walk property using the LaMotte-McWother test. And for structural breaks, we employ the fluctuations test (Ploberger et al., 1989). Finally, we again use our general to specific approach to estimate (2.8); starting off with lag lengths of nine and p=q, and dropping those lags which were never significant (as we did before).[5]

Having estimated the coefficients in (2.8), we can calculate the gain, coherence and cross spectra based on the time-varying spectra just obtained. That allows us to overcome a major difficulty in this kind of analysis: namely that a very large number of observations would usually be necessary to carry out the necessary frequency analysis by direct estimation. This may be a particular problem in the case of structural breaks, since the sub-samples would typically be too small to allow the associated spectra to be estimated directly.

In Hughes Hallett and Richter (2002; 2003a; 2003b; 2004) we use the fact that the time-varying cross spectrum, $f_{YX}(\omega)_t$, using the STFT is given by

$$f_{YX}(\omega)_t = \left|A(\omega)\right|_t f_{XX}(\omega)_t \tag{2.9}$$

where $A(\omega)$ is the gain which is calculated using the short time Fourier transform of the weights $\left\{a_j\right\}_{j=-\infty}^{\infty}$. As noted above, the traditional formulae can be used to do this at each point in time. The last term in (2.9), $f_{XX}(\omega)_t$, is the spectrum of the predetermined variable. Hence this spectrum may be time varying as well. Next, we calculated the gain according to

$$\left|A(\omega)\right|_t = \left|\sqrt{\left(\frac{\sum_{b=1}^{q} a_{b,t} \exp(-j\omega b)}{1-\sum_{i=1}^{p} v_{i,t} \exp(-j\omega i)}\right)^2}\right|_t, \text{ for b=1...q and i=1...p} \tag{2.10}$$

which is time-varying as well. However in this paper we are interested in the coherence, and in the decomposition of the changes to that coherence over time. So we need to establish a link between the coherence and the gain. The spectrum of any dependent variable is defined as (Jenkins and Watts, 1968; Laven and Shi, 1993; Nerlove et al., 1995; Wolters, 1980):

$$f_{YY}(\omega)_t = \left|A(\omega)\right|_t f_{XX}(\omega)_t + f_{VV}(\omega)_t \tag{2.11}$$

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[5] The symmetry in the lag structure, and our general to specific testing strategy, means that we can allow the data to determine the direction of causality in these regressions. We find that EMU leads the individual countries (see tables 9-15). Since the reverse causalities were not accepted, we do not report coherences for those cases.

where $f_{VV}(\omega)_t$ is the time-varying residual spectrum and $f_{YY}(\omega)_t$ is the time varying spectrum of the endogenous variable.

Given knowledge of $f_{YY}(\omega)_t$, $\left|A(\omega)\right|^2$, and $f_{XX}(\omega)_t$, we can now calculate the coherence as

$$K^2_{YX,t} = \frac{1}{\left\{1 + f_{VV}(\omega)_t \middle/ \left(\left|A(\omega)\right|_t f_{XX}(\omega)_t\right)\right\}} \tag{2.12}$$

The coherence is equivalent to the R^2 of the time domain. The coherence measures, for each frequency, the degree of fit between X and Y: or the R^2 between each of the corresponding cyclical components in X and Y. Hence, the coherence measures the link between two variables at time t. For example, if the coherence has a value of 0.6 at frequency 1.2, then this means that country X's business cycle at a frequency of 1.2 determines country Y's business cycle *at this point in time* by 60%. The coherence does not take into account a shift in the business cycle, e.g. if the European business cycle leads the German one by 1 quarter. In this paper, we are concerned only with the coherence, not the gain or phase shift elements.

The next question is, in which cyclical components do structural breaks or changes in behaviour appear? We define structural changes as changes that occur in the underlying relationship between two variables. To identify such changes, we reformulate the coherence. Solving (2.11) for $f_{VV}(\omega)$, and substituting the result into (2.12), yields:

$$\begin{aligned} K^2_{XY,t} &= \frac{1}{\left\{1 + \left(f_{YY}(\omega)_t - \left|A(\omega)\right|_t f_{XX}(\omega)_t\right) \middle/ \left(\left|A(\omega)\right|_t f_{XX}(\omega)_t\right)\right\}} \\ &= \left|A(\omega)\right|_t \frac{f_{XX}(\omega)_t}{f_{YY}(\omega)_t} \end{aligned} \tag{2.13}$$

Finally, defining $$\frac{f_{XX}(\omega)_t}{f_{YY}(\omega)_t} = f_{DD}(\omega)_t, \tag{2.14}$$

we get $$K^2_{YX,t} \equiv \left|A(\omega)\right|_t f_{DD}(\omega)_t \tag{2.15}$$

This last equation, (2.15), allows us to analyse structural changes in the coherence between X and Y. We can now write the changes in the coherence as:

$$\Delta K^2_{XY,t} = \Delta \left| A(\omega) \right|_t \Delta f_{DD}(\omega)_t \tag{2.16}$$

As shown in Hughes Hallett and Richter (2002; 2003a; 2003b; 2004), (2.16) may be obtained from (2.10), (2.12), and the single variable spectra of section 3 needed to generate (2.14).

Last, but not least, a note on the figures shown in the following two sections. We first present the time-varying spectra and then the coherences. One can see from these figures that the spectra change. However, one cannot infer directly from those figures that the changes in the spectra are also statistically significant. The figures for the time-varying spectra have to be accompanied by the fluctuation test results. Once a structural break has been identified by the fluctuations test, the results of that will show up as significant in the associated spectrum.

3 Single Spectra

In this section and the next, we study the spectra and cross-spectra of output growth in seven of the Euro area economies over the past 25 years. We take France, Germany and the Netherlands to represent the original "core" economies; Italy, Spain and Finland to represent three different types of "periphery" economy; and Sweden as a representative "out" economy. Similar results for the US and the UK, and for the Eurozone as a whole, will be found in Hughes Hallett and Richter (2006) and can be used as a benchmark for these comparisons. We use quarterly, seasonally adjusted data for real GDP in all seven economies, as published in the *OECD NAQ (national Accounts quarterly) database*, and then log difference them once to obtain growth rates. The resulting series were then fitted to an AR(p) model as described above, and tested for stationarity, statistical significance and a battery of other diagnostic and specification checks. Our sample starts in 1980Q1 and finishes in 2005Q1 in each case.

We use data consistent with the ESA 95 (European System of Accounts) definitions. The ESA 95 was introduced as an improvement on the previous system of national accounts data, which dated from 1979. Progress has been made in the harmonisation of methodology, and in the precision and accuracy of the concepts, definitions, classifications and accounting rules needed to arrive at a consistent, reliable and comparable quantitative description of the economies of the Member States. The 1995 ESA is also fully consistent with the revised world-wide guidelines on national accounting, the System of National Accounts (1993 SNA, produced by the United Nations, the IMF, the Commission of the European Communities, the

OECD and the World Bank). However, the ESA is focused more on the circumstances and data needs in the European Union. Like the SNA, the ESA is harmonised with the concepts and classifications used in many other, social and economic statistics. For the purpose of this paper some changes are important: for example, the introduction of a new concept of final consumption: actual final consumption; the introduction of a new price-adjusted income concept: real national disposable income; and the inclusion of purchasing power parity measures.

3.1 *Italy*

The Italian spectrum shows very little volatility in the Italian economy at any frequency until 1999 (Figure 1). At that point, output volatility (as reflected in growth rates) doubles compared to earlier years. This volatility is concentrated on two cycles, the business cycle (3-4 year cycles) and short run cycles (6 months-1 year). Thus membership of the Euro seems to have disturbed the Italian economy significantly, causing either a great deal of adjustment or a great deal of being buffeted by changes and shocks that the economy was no longer able to cope with. However that effect seems to have subsided after 2003 (reform fatigue?), leaving an economy with high persistence in the longer cycles rather like France. Before EMU there is a period of lesser volatility around 1993-7, presumably reflecting the adjustments necessary to qualify for Eurozone membership. The fact that those adjustments caused small changes relative to what came afterwards (in the Euro period) suggests that these reforms turned out to be inadequate or incomplete. The period before the Maastricht treaty shows very little volatility or change in Italian growth, except briefly at the time of German unification. During the years of the Euro, volatility is increasing, although recently the density of the two most common business cycles returned to their values they had prior to joining the Euro. The sample ends in 2010Q4, so it seems that Italy had “digested” the financial crisis. Indeed, Italian banks were not as affected by the financial crisis as banks in UK or Germany. On the other hand, the sample stops well before Italy was downgraded. So it is not unlikely to assume that the business cycle characteristics may change due to the downgrading of Italy. Although, one can only answer this question once more data is available.

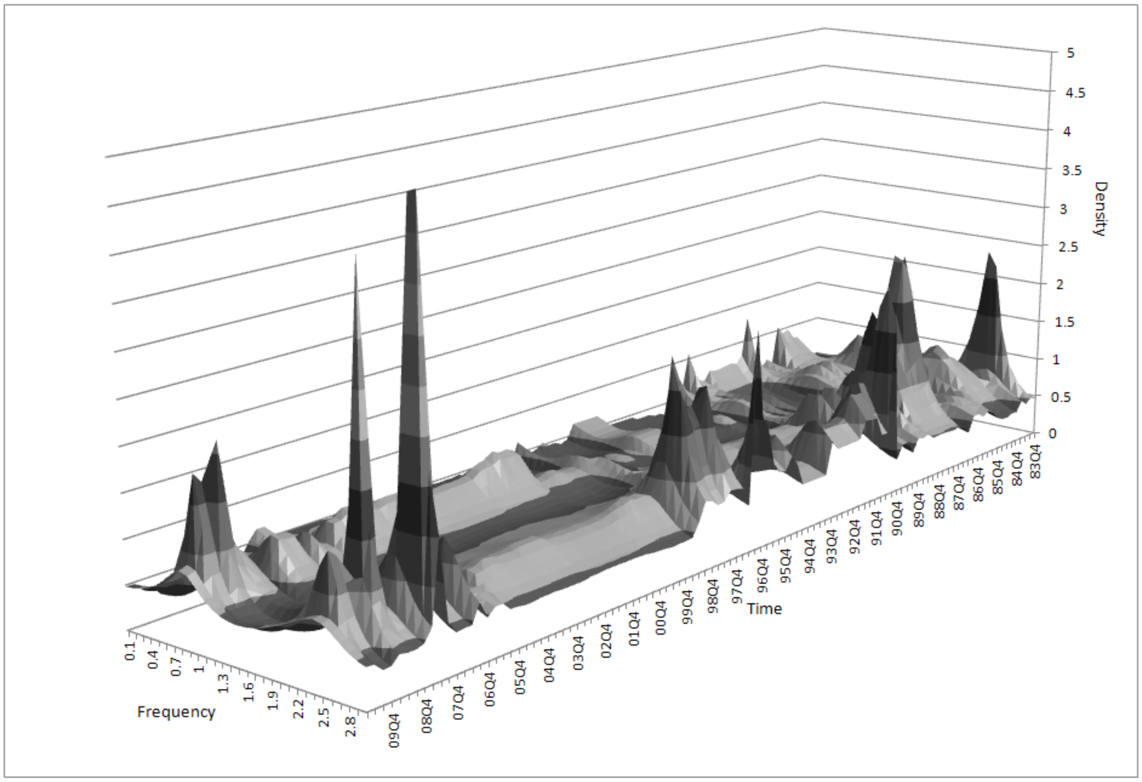

Figure 1: The Italian Spectrum

3.2 *Spain*

The main characteristics of the Italian spectrum also hold for the Spanish spectrum (Figure 2). One can observe a large volatility up to the introduction of the Euro and the first years of the Euro. The introduction of the Euro led to a different business cycle to emerge namely, at a frequency of around 2.1. This business cycle was present before, but now it density is increasing a lot, implying that its importance is growing.

Over the last two years of the sample, the long term trend re-emerged as the main component of the business cycle, although its importance is not (yet) as high as it used to be. Still, it emerged after the financial crisis in 2008 as the most important cycle component. Hence, like in the case of Italy, the business cycle changed back to what it was prior to joining the Euro. The financial crisis seemed to have been digested rather well, just before the latest turmoil broke out.

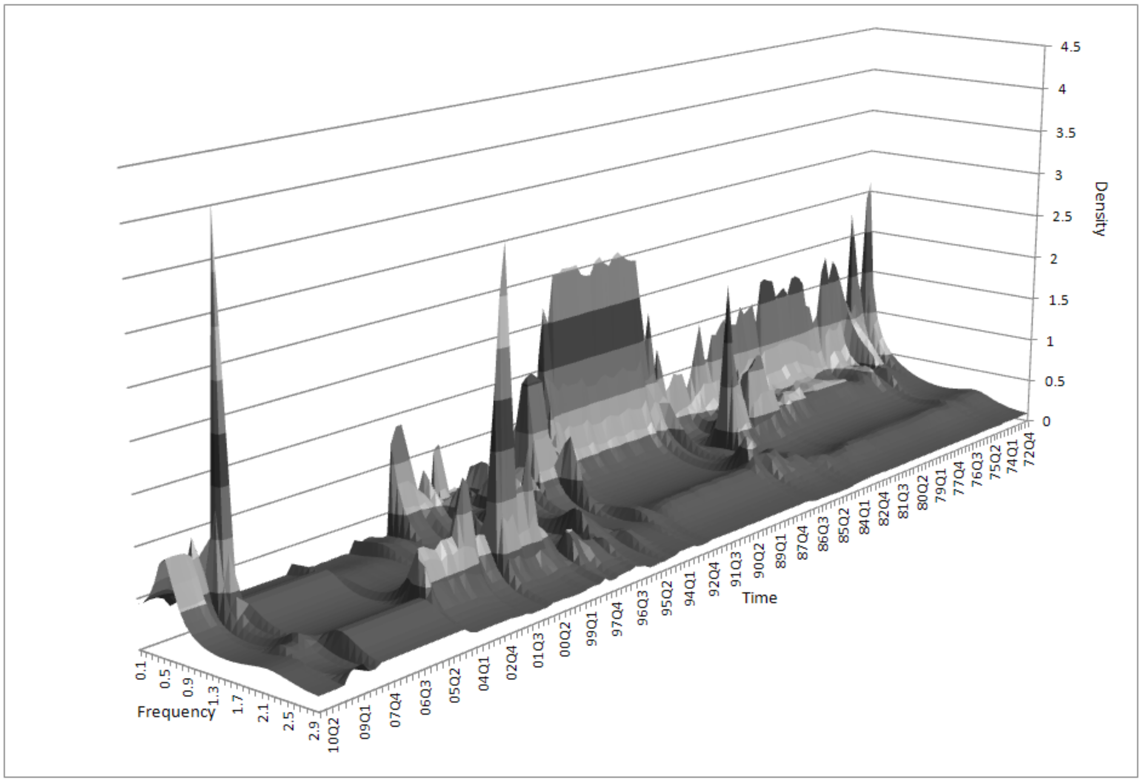

Figure 2: The Spanish Spectrum

3.3 *Ireland*

The story for Ireland is similar to the previous countries (Figure 3). Prior to the introduction of the Euro, the long run trend wasthe most important feature of the Irish business cycle. However, short term uncertainty was also high. Once the Euro was introduced, the characteristics changed completely and the business cycle became more volatile. Although, the short term uncertainty disappeared and never gained its prolonged importance again. However, other cycles gained for some periods importance and then lost their imporatnvce again. This only changed in 2009 where three cycles emerged: at 0.9, 1.7 and 2.5. So prior to the recent turmoil, the business finally converged to a less volatile state.

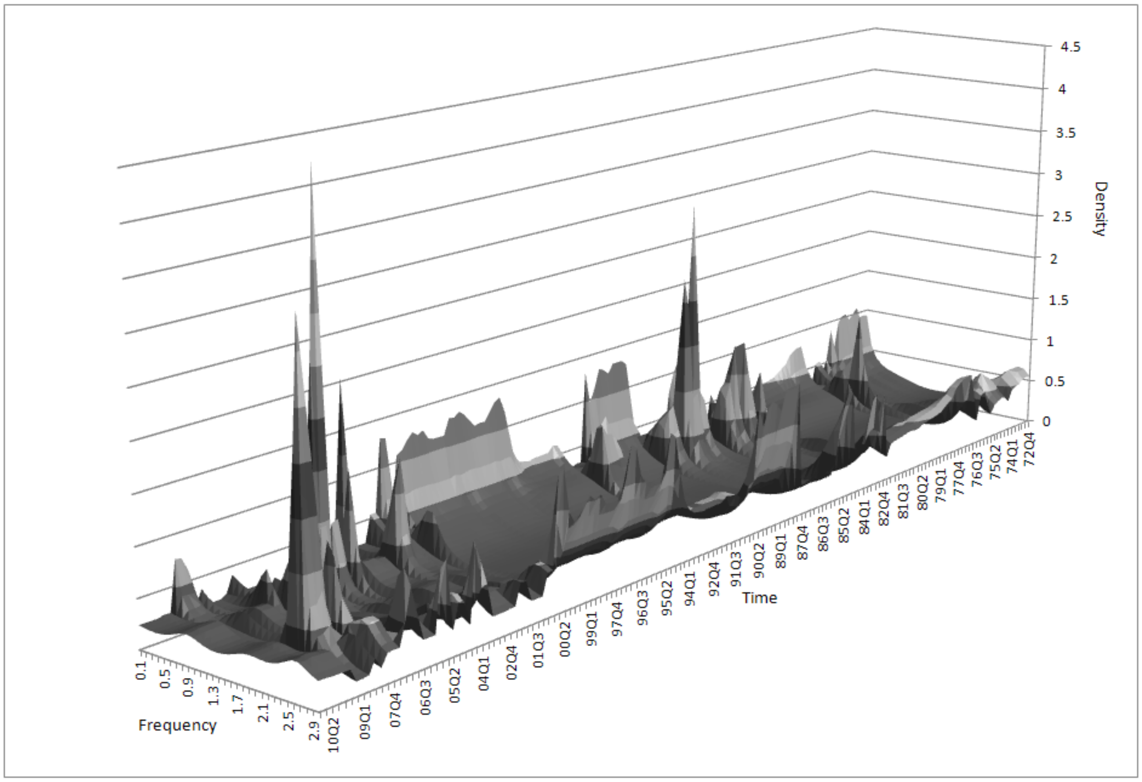

Figure 3: The Irish Spectrum

3.4 *Portugal*

The spectrum of the Portuguese business cycle is remarkably smooth starting in 1995 (Figure 4). Short term uncertainty is important throughout the sample, but also a cycle at a frequency of 0.6. The Portuguese economy does not seem to be affected by the financial crisis in terms of its business cycle characterstics (of course Portugal went into recession as well, but this did not change the business cycle per se). Only the EU accession in 1985 had an impact on the business cycle characteristic. As in the other cases, the Portuguese data sample ends in 2010Q4, so we cannot really say whether the recent turmoil had an impact on the business cycle characteristics, but what is remarkable is that up to 2010Q4 the spectrum does not I indicate a forthcoming change.

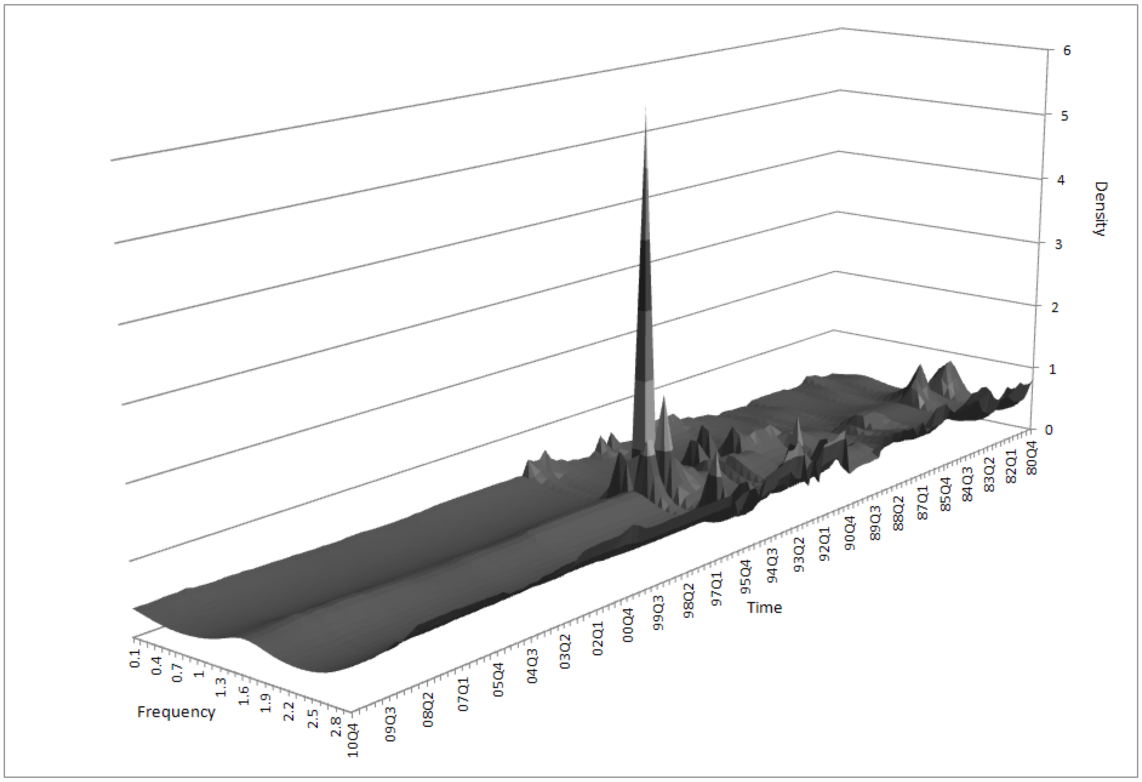

Figure 4: The Portuguese Spectrum

3.5 *Greece*

Greece is, of course, the country most affected by the recent turmoil. However, like Portugal, the Greek spectrum is fairly stable throught the sample (Figure 5). There are periods where the Greek business cycle is volatile, for example before 1990 and then just before the introduction of the Euro. Towards the end of the sample the spectrum seems to change. This may be interpreted as the first signs of the beginning financial problems Greece is facing.

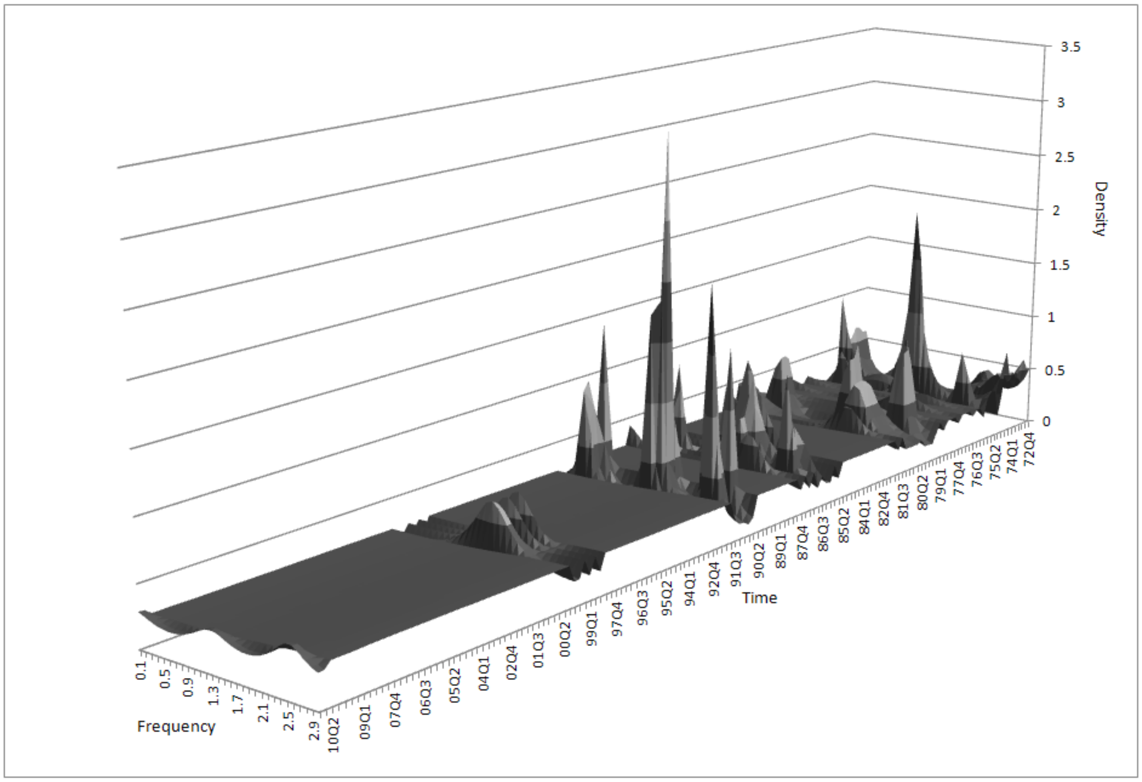

Figure 5: The Greek Spectrum

3.6 *Summary*

The individual spectra show that the southern European countries are quite different from eacht other, although there are also similarities. Greece and Portugal have in common that their business cycles were relatively calm over prolonged periods, whilst the business cycles of Spain, Ireland and Italy were much more volatile. The fact that countries still have their own business cycle characteristics confirms a result we had found earlier (Hughes Hallett and Richter, 2006; 2008). It also highlights the fact that reason for current problems of the southern European countries are more of individual nature than common failures. Indeed although they have in common an unsustainable deficit, the source of the deficit is different from one country to another.

So the next section will look at the link between those countries and the Eurozone.

4 Convergence of the PIIGS Business Cycles with the Eurozone?

We turn now to the coherence, or correlations, between the economic cycles of our Eurozone economies – and whether those coherences have been increasing or decreasing. These results will supply an informal test of the popular hypotheses that the Eurozone economies are well converged cyclically (at least better converged than with those outside the Eurozone), and whether their degree of convergence has increased with membership of the Eurozone as the European Commission and many others contend?[6] More specifically, we can test the proposition that, if exchange rates are pegged, then business cycles will converge as trade and financial links intensify. This is an important matter. Artis and Zhang (1997) and Frankel and Rose (1998, 2002) argue that this will happen as the trade and financial links strengthen; while Kalemli-Ozcan et al (2001, 2003), Hughes Hallett and Piscitelli (2002), Baxter and Kouparitsas (2005), Peersman and Smets (2005) and Belke and Heine (2006) show that it has not happened or may very well not happen.

This section adds empirical evidence on this issue, with the addition that we can show the frequencies at which convergence is occurring. This extra twist is important since disagreements in the literature may have arisen because convergence has occurred at certain frequencies and not others, implying that the average correlations may have increased when the vital correlations at the business cycle frequency have gone down (or vice versa). We are principally interested in coherence at the business cycle frequency because of what it implies will be demanded of policy making and market responsiveness (and price and wage flexibility in particular); but short and long cycle coherences are important too for their ability to transmit shocks.

To assess cyclical convergence in the EU, we take each country in our sample against the Eurozone average (rather than any particular country) since monetary policy has to be designed for that average. We then compute the coherence at different times and at different cycle lengths from the associated cross-spectra.

[6] See, for example, European Commission (1990), Altavilla (2004).

4.1 *Italy and the Eurozone*

We firstly investigate Italy's link with the Eurozone (Figure 6). The coherence is in shape more stable than Italy's spectrum. The long run trend the most common feature between the Eurozone and Italy.

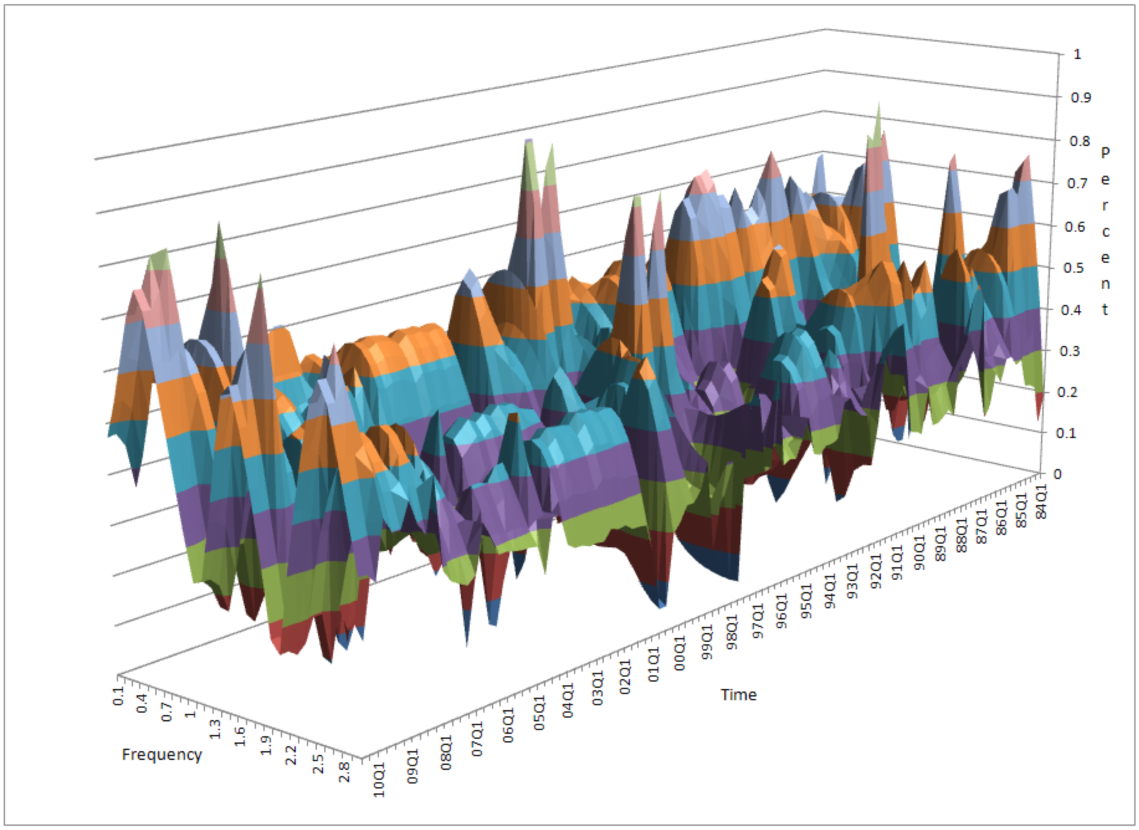

Figure 6: Coherence between Italy and the Eurozone

At the beginning of the sample, there were mainly two cycles important to both areas: the long run trend and a cycle at around 1.3. From the beginning of the 1990s short term uncertainty became more and more important. At the end of the sample the short run cycle is slightly more important than the medium cycle.

Since the financial crisis in 2008, there is a shift upwards recognisable, increasing the coherence between Italy and the Eurozone. Although, this increase peaked in 2009. However, the three cycles can be explained by 70% down to about 60% by the Eurozone cycles. This is still higher than at the beginning of thesample. Yet, many Italian cycles cannot be explained by the Eurozone behaviour. So the result is that at least as a shor term effect the financial crisis of 2008 has led to a higher convergence, but not full convergence and is stagnating since.

4.2 *Spain and the Eurozone*

The following Figure 7 shows the development of the coherence between Spain and the Eurozone.

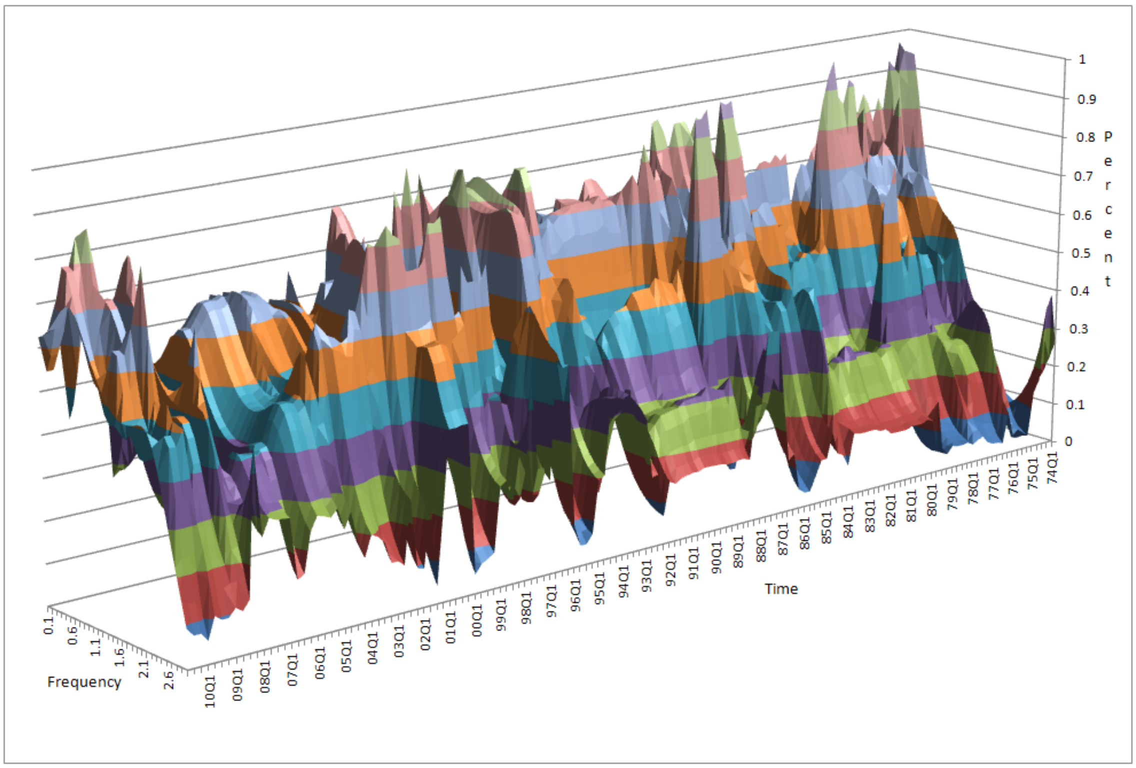

Figure 7: Coherence between Spain and the Eurozone

As in the previous case, the long run trend is the cycle which is most closely related to the Eurozone. Although, during the 2000s the trend loses importantance from about 80% down to 60%. But after the financial crisis in 2008 the long run trend increases to 80% again, though it has since declined a bit. In contrast to Italy, joining the Euro meant that the Eurozone cycles cannot explain short term uncertainty anymore. Uncertainty therefore enters the Spanish business cycles from other sources than the Eurozone. So to an extent, joining the Eurozone had a stabilising effect. The other two remaining cycles are at frequencies of 1.1 and 2.3 respectively. Like in Italy, the medium cycle only emerged with Eurozone. So to another extent, the Eurozone led more converngence by determining another business cycle.

Over the entire frequency band though, many cycles cannot or only partly be explained by the Eurozone behaviour.

Towards the end of the sample, there is change of the coherence visible. So it is possible, that the turmoil caused by the fiscal policies spill over into the link between Spain and the Eurozone.

4.3 *Ireland and the Eurozone*

The coherence between Ireland and the Eurozone has been relatively high (up to 90%) at the beginning of the sample and then declined for most cycles until 2008 when they finally picked up again. So like in the case of Italy and Spain, the 2008 financial crisis led to an increased converegence, which did not remain stable. Since then they have declined to about 70%. Whilst in the beginning the coherence between the Eurozone and the Irish short term cycle is fairly small, this link increased after 2008.

It is remarkable though that not the introduction of the Euro led to bigger convergence of Ireland towards the Eurozone cycle, but the financial crisis 2008. It seems that only a massive outside shock can cause business cycles to converge, but not the introduction of a common currency per se. Although, the common currency provides a certain basis in this case which is not undercut for prolonged periods.

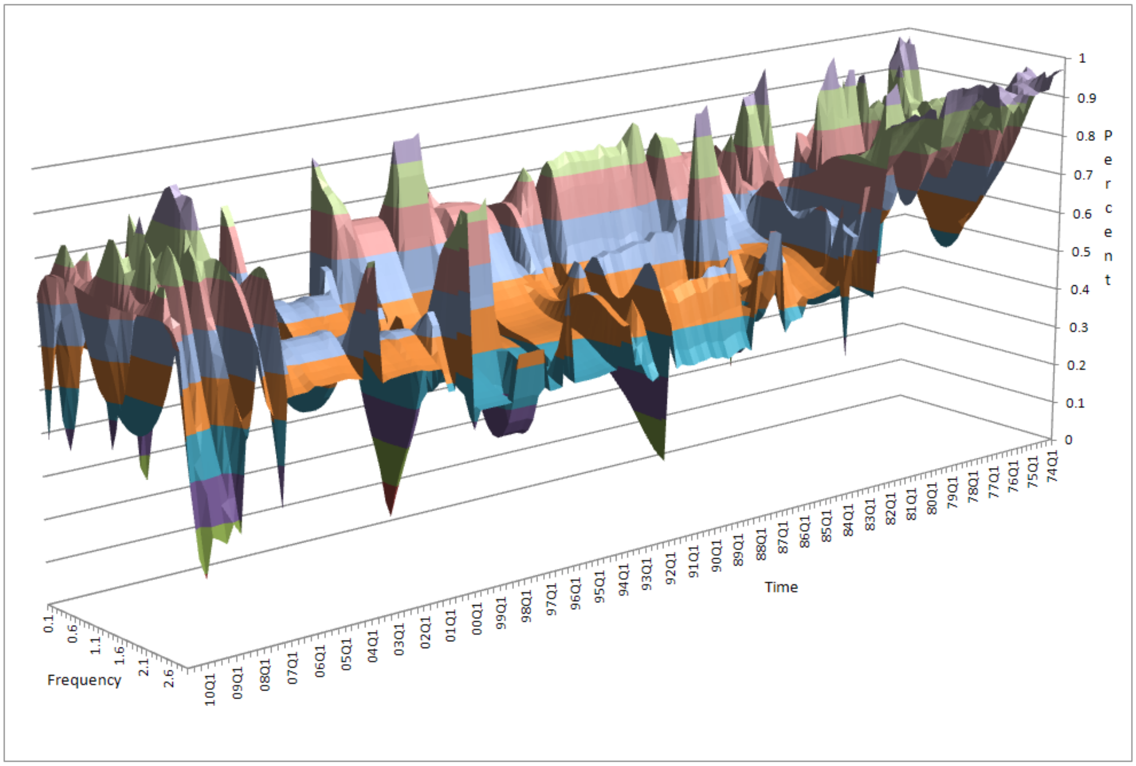

Figure 8: The Coherence between Ireland and the Eurozone

4.4 *Portugal and the Eurozone*

Before the euro was introduced the Portuguese link with the Eurozone was quite volatile (Figure 9). After the introduction of the Euro three links with the Eurozone emerged: at a frequency of 0.2, 0.9 and 2.5. These cycle links remained stable at around 60% until the 2008 crisis. So the Eurozone contributed 60% to these Portuguese cycles. The immediate effect of the financial crisis was an increase of the coherence to about 70%. Like in the previous countries, the coherence then decreased but stayed at a higher level than before the 2008 crisis. Recently, the coherence sunk further and for the long run trend there seems to be a new link emerging. Like in the previous cases, the Euro did not lead to an increase of the convergence, but to a stabilisation of the existing links.

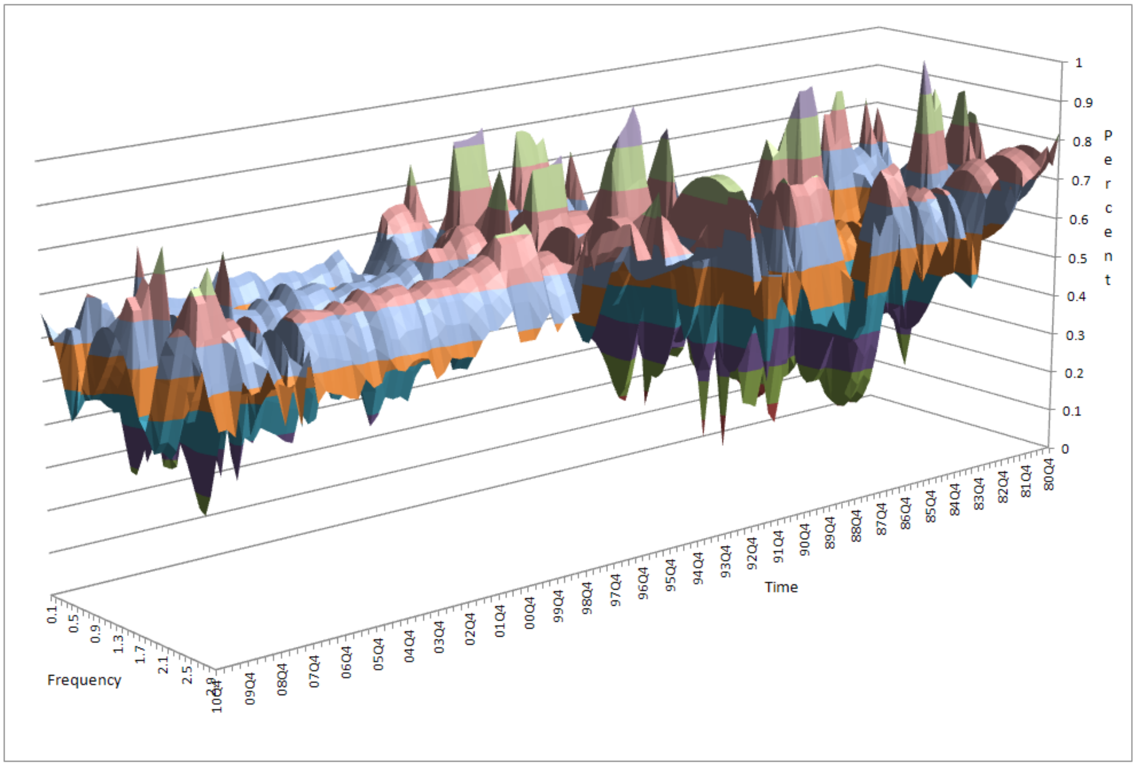

Figure 9: The Coherence between Portugal and the Eurozone

4.5 *Greece and the Eurozone*

In difference to all other countries, the coherence between Greece and the Eurozone has never been stable for a prolonged period (Figure 10). Although, there are three main links especially towards the end of the sample: 0.3, 1.6 and 2.6. There is no convergence process visible, but some Greek (long run) cycles are sometimes up to 90% determined by the Eurozone. Like in the previous cases, the immediate reaction to 2008 crisis was an increase in the coherence and – as before – this increase was short lived. The Euro had obviously no strong stabilising effect like in Portugal and Italy although volatility was reduced. Interestingly, just at the end of the sample, the coherence sinks even further which could be a first indicaiton of the turmoil to come. If this is true, then we have the paradox situation that some crises lead to an increase in convergence whilst others lead to a decrease of the convergence. This may reflect a future research agenda of what crises cuase an increase and what crises cause a decrease of the coherence.

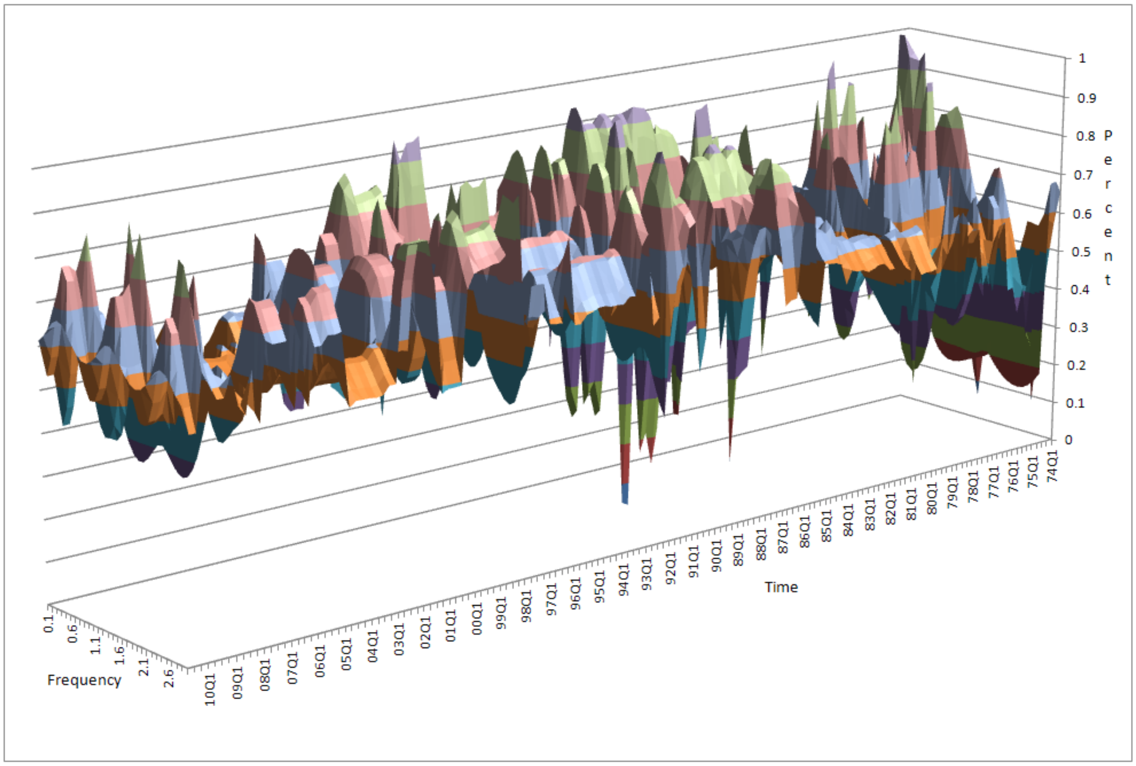

Figure 10: Coherence between Greece and the Eurozone

5 Conclusion

This paper has made four contributions. First we have presented a technique by which business cycles can be decomposed into their component cycles and compared; and we have shown how to do that when the component cycles, and their relative importance, are allowed to vary over time. As a result, we found that the individual data generating processes have varied across the PIIGS countris. Thus one neoclassical assumption for a common growth pattern is not fulfilled.

Second, we have shown how to extend this univariate analysis in order to determine the coherence between different cycles in different economies, and allow that coherence to vary over time.

Third we have shown how to apply these methods to answer the question: is there an emerging convergence process? As expected there is a certain amount in common between the PIIGS countries and the rest of the Eurozone; but that is mostly in a mildly declining convergence at the business cycle frequencies, and in a shift from convergence at business cycles to a greater shared volatility at short cycles.

We find that in some case the introduction of the Euro has not led to an increased convergence, but to a more stable relationship at the existing levels. We also found that the 2008 crisis led initially to a greater convergence which was successively reduced. For Greece in particular, it seems that the 2008 crisis led to an increase in the coherence, whilst the recent crisis leads to a decrease of the coherence.

The conclusion from these results must be that there is no general convergence as such within the PIIGS and the Eurozone countries. The introduction of the Euro is per se no sufficient condition for convergence of business cycles. However, financial crises can change the business cycle characteristics. In some case they can cause convergence (however short lived), but they can also cause divergence.

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Appendix 1: The Statistical Results

Note: For reasons of space, the results quoted in the tables describe the final regression done and its diagnostic tests. But the figures which follow display the period by period spectral results implied by the underlying time-varying regressions.

VAR/System - Estimation by Kalman Filter			
Dependent Variable	DLITGDP	Quarterly Data From	1982:01 To 2010:04
Usable Observations	116	Degrees of Freedom	111
Uncentered R^2	0.98092		
Mean of Dependent Variable	0.352425	Std Error of Dependent Variable	0.677123819
Standard Error of Estimate	0.702126		
Akaike Information Criterion:	0.78848	Ljung-Box Test: Q*(21) =	26.7368
Variable	Coeff	Std Error	T-Stat
Constant	0.246548	0.745745138	0.330606
DLITGDP{1}	0.035369	0.189799991	0.186347
DLITGDP{3}	0.056241	0.252509197	0.22273
DLITGDP{4}	-0.25243	0.146903312	-1.71836
DLITGDP{7}	0.061571	0.018344555	3.356344

Table 1: Italian Regression Results

VAR/System - Estimation by Kalman Filter			
Dependent Variable	DLITGDP	Quarterly Data From	1982:01 To 2010:04
Usable Observations	116	Degrees of Freedom	107
Uncentered R^2	0.90158		
Mean of Dependent Variable	0.352425	Std Error of Dependent Variable	0.677123819

Standard Error of Estimate	0.67322		
Akaike Information Criterion:	0.7941	Ljung-Box Test: Q*(22) =	20.9669.
Variable	Coeff	Std Error	T-Stat
Constant	-0.35883	0.27968795	-1.28296
DLITGDP{3}	0.100297	0.018073126	5.549508
DLITGDP{7}	-0.13679	0.198063596	-0.69065
DLEMUITGDP	0.788754	0.166669333	4.732449
DLEMUITGDP {1}	0.116834	0.015134552	7.719675
DLEMUITGDP {2}	-0.09904	0.073910614	-1.33998
DLEMUITGDP {4}	-0.14892	0.140397755	-1.06073
DLEMUITGDP {6}	-0.00288	0.147931319	-0.01949
DLEMUITGDP {7}	0.035281	0.20938230	0.168498

Table 2: Regression Results between Italy and EMU

VAR/System - Estimation by Kalman Filter			
Dependent Variable	DLSPGDP	Quarterly Data From	1970:01 To 2010:04
Usable Observations	156	Degrees of Freedom	150

Uncentered R^2	0.88133		
Mean of Dependent Variable	2.23912	Std Error of Dependent Variable	1.704865068
Standard Error of Estimate	1.355759		
Akaike Information Criterion:	1.46489	Ljung-Box Test: Q*(25) =	23.6642.
Variable	Coeff	Std Error	T-Stat
Constant	-0.02891	0.234215397	-0.12343
DLSPGDP{1}	0.64055	0.263259083	2.433156
DLSPGDP{2}	0.104304	0.188378419	0.553692
DLSPGDP{3}	0.072911	0.189906648	0.383931
DLSPGDP{4}	-0.30345	0.022228481	-13.6516
DLSPGDP{5}	0.038818	0.205487945	0.188907

Table 3: Spanish Regression Results

VAR/System - Estimation by Kalman Filter			
Dependent Variable	DLSPGDP	Quarterly Data From	1970:01 To 2010:04
Usable Observations	156	Degrees of Freedom	147
Uncentered R^2	0.89994		
Mean of Dependent Variable	2.23912	Std Error of Dependent Variable	1.704865068
Standard Error of Estimate	1.333652		
Akaike Information	1.441	Ljung-Box Test: Q*(25) =	32.4742

Criterion:			
Variable	Coeff	Std Error	T-Stat
Constant	-0.02029	0.177672579	-0.1142
DLSPGDP{1}	0.361715	0.284639167	1.270786
DLSPGDP{2}	-0.0573	0.149192081	-0.38405
DLSPGDP{3}	0.22789	0.172418033	1.321731
DLSPGDP{4}	-0.26151	0.016916658	-15.4585
DLSPGDP{5}	0.214616	0.177551622	1.208752
DLEMUSPGDP	0.32043	0.049374619	6.489773
DLEMUSPGDP {1}	0.112321	0.148653477	0.75559
DLEMUSPGDP {3}	0.033345	0.198342889	0.16812

Table 4: Regression Results between Spain and EMU

VAR/System - Estimation by Kalman Filter			
Dependent Variable	DLIRGDP	Quarterly Data From	1972:01 To 2010:04
Usable Observations	156	Degrees of Freedom	150
Uncentered R^2	0.75977		
Mean of Dependent Variable	1.079566	Std Error of Dependent Variable	1.339284876
Standard Error of Estimate	2.239013		
Akaike Information Criterion:	2.41924	Ljung-Box Test: Q*(25) =	35.7904
Variable	Coeff	Std Error	T-Stat

Constant	-0.44882	0.816295978	-0.54982
DLIRGDP{1}	-0.17527	0.065142775	-2.69051
DLIRGDP{2}	0.263722	0.442398586	0.596119
DLIRGDP{3}	-0.22071	0.400630997	-0.55091
DLIRGDP{4}	-0.0986	0.028331182	-3.48023
DLIRGDP{7}	0.112007	0.027385	4.09009

Table 5: Regression Results for Ireland

VAR/System - Estimation by Kalman Filter			
Dependent Variable	DLIRGDP	Quarterly Data From	1972:01 To 2010:04
Usable Observations	156	Degrees of Freedom	147
Uncentered R^2	0.76824		
Mean of Dependent Variable	1.079566	Std Error of Dependent Variable	1.339284876
Standard Error of Estimate	1.384632		
Akaike Information Criterion:	1.49609	Ljung-Box Test: Q*(24) =	20.0627
Variable	Coeff	Std Error	T-Stat
Constant	0.451827	0.55127534	0.81960
DLIRGDP{1}	-0.26139	0.39768011	-0.6573
DLIRGDP{2}	0.722004	0.42309255	1.706491
DLIRGDP{3}	0.153604	0.60479636	0.253976
DLIRGDP{4}	-0.05753	0.0230754	-2.49301

DLIRGDP{6}	0.117136	0.42325363	0.276751
DLEMUIRGDP	0.946603	0.17680525	5.353928
DLEMUIRGDP {2}	-1.07562	0.66614537	-1.61469
DLEMUIRGDP {3}	0.286891	0.24544726	1.168851

Table 6: Regression Results between Ireland and the EMU

VAR/System - Estimation by Kalman Filter			
Dependent Variable	DLPTGDP	Quarterly Data From	1979:01 To 2010:04
Usable Observations	128	Degrees of Freedom	124
Uncentered R^2	0.81687		
Mean of Dependent Variable	0.496621	Std Error of Dependent Variable	1.938206991
Standard Error of Estimate	1.853817		
Akaike Information Criterion:	1.97338	Ljung-Box Test: Q*(22) =	31.4291.
Variable	Coeff	Std Error	T-Stat
Constant	0.032789	0.6880207	0.047657
DLPTGDP{1}	-0.16641	0.092170325	-1.80549
DLPTGDP{4}	0.22603	0.124453652	1.81618
DLPTGDP{5}	-0.28273	0.258173444	-1.0951

Table 7: Regession Results for Portugal

VAR/System - Estimation by Kalman Filter

Dependent Variable	DLPTGDP	Quarterly Data From	1979:01 To 2010:04
Usable Observations	128	Degrees of Freedom	123
Uncentered R^2	0.86338		
Mean of Dependent Variable	0.496621	Std Error of Dependent Variable	1.938206991
Standard Error of Estimate	1.810227		
Akaike Information Criterion:	1.92698	Ljung-Box Test: Q*(22) =	34.3726
Variable	Coeff	Std Error	T-Stat
Constant	-0.08352	0.207226091	-0.40303
DLPTGDP{1}	-0.26465	0.111880555	-2.36547
DLPTGDP{4}	-0.03858	0.416383082	-0.09266
DLEMUPTGDP	0.830128	0.288073337	2.881654
DLEMUPTGDP {5}	0.249278	0.054490646	4.574698

Table 8: Regression Results between Portugal and the Eurozone

VAR/System - Estimation by Kalman Filter			
Dependent Variable	DLGRGDP	Quarterly Data From	1972:01 To 2010:04
Usable Observations	156	Degrees of Freedom	150
Uncentered R^2	0.9137		
Mean of Dependent Variable	0.542049	Std Error of Dependent Variable	2.846833578
Standard Error of Estimate	4.068511		

Akaike Information Criterion:	4.39601	Ljung-Box Test: Q*(24) =	32.4866
Variable	Coeff	Std Error	T-Stat
Constant	-0.48466	0.565640583	-0.85684
DLGRGDP{1}	-0.15926	0.035886505	-4.43779
DLGRGDP{2}	0.396176	0.297772522	1.330466
DLGRGDP{4}	0.081532	0.176450863	0.462067
DLGRGDP{5}	0.202232	0.115473529	1.751331
DLGRGDP{6}	0.41705	0.311061572	1.340733

Table 9: Regression Results for Greece

VAR/System - Estimation by Kalman Filter			
Dependent Variable	DLGRGDP	Quarterly Data From	1972:01 To 2010:04
Usable Observations	156	Degrees of Freedom	148
Uncentered R^2	0.94872		
Mean of Dependent Variable	0.542049	Std Error of Dependent Variable	2.846833578
Standard Error of Estimate	4.260617		
Akaike Information Criterion:	4.60358	Ljung-Box Test: Q*(24) =	23.5444
Variable	Coeff	Std Error	T-Stat
Constant	-0.11597	0.520061883	-0.223
DLGRGDP{1}	0.26073	0.305951257	0.852193
DLGRGDP{2}	0.761752	0.477559574	1.595093

DLGRGDP{4}	-0.07395	0.314777825	-0.23493
DLGRGDP{6}	-0.1452	0.042082208	-3.45028
DLEMUGRGDP	0.395863	0.125005937	3.166756
DLEMUGRGDP{2}	0.089986	0.456952439	0.196927
DLEMUGRGDP{6}	0.481573	0.418070987	1.151894

Table 10: Regression Results for Greece and the Eurozone