Structural Similarity as a Determinant of Business Cycle Synchronization in the European Union: A Robust Analysis

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Abstract

This paper presents evidence of the significant impact of structural similarities on business cycle synchronization. Using Sala-i-Martin's methodology (1997a; 1997b), proven correlation coefficients of structural shares are offered as robust determinants of business cycle synchronization. The results are not only robust across different levels of disaggregation, but also for value added and employment shares. The results are not robust across measures. The linear measure has proven to be a bad proxy for structural similarities as a determinant of business cycle synchronization. The degree of convergence is also a robust determinant of business cycle synchronization, with the negative point estimate. This might be explained by Imbs and Wacziarg's U-Shape specialization curve. Convergence might lead to higher business cycle synchronization through the channel of specialization. This notion is confirmed by the results of simultaneous equations estimation. Finally, evidence is found that higher structural similarities can better foster a similar response to external exogenous economic shocks.

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1. Introduction

Current financial and debt crisis in the euro area once more reminds us of the importance of conditions that allow the European Central Bank to use monetary policy efficiently. Optimum currency area theory suggests that it is possible when business cycles of countries integrated under one currency are fairly synchronized. This paper tries to uncover the significance of sectoral specialization as a determinant of business cycle synchronization using the Sala-i-Martin approach to extreme bounds analysis (1997a; 1997b). Beside a set of M variables previously used in the literature, two new ones are proposed. Firstly, as suggested by Lehwald (2012), higher business cycle synchronization in the euro area might come from general tendencies in the world rather than from economic processes within the Eurozone. To assess the validity of his argument, the impact of the US economy on European Union business cycle synchronization is assessed. Secondly, Imbs and Wacziarg (2003) have shown that higher convergence of real income leads to a U-shaped structural similarity function. This suggests that the level of convergence might also impact business cycle synchronization in different ways, depending on specific country real GDP *per capita*. And finally, most papers that focus their attention on the importance of structural similarities have used data concerning 6 sectors (Böwer and Guillemineau, 2006; Siedschlag 2010; Dées and Zorell, 2011). In this paper the impact of structural similarities is analysed at various levels of disaggregation – from 3 sectors to 2 digit level sectors, using shares of value added and employment. All the data used comes from the period between 1990 and 2007, with exceptions mentioned later in the text.

To measure business cycle synchronization, the Baxter-King band pass filter (Baxter and King, 1999) is used on real GDP time series. This filter seems to be an appropriate choice due to the fact that it retains both high and low frequencies, so components of GDP cannot be influenced by monetary policy. The filtered data is then used to calculate bilateral correlation coefficients for 20 European Union countries. All explanatory variables are also expressed pairwise for the 20 European Union countries. To examine the impact of different determinants, an extreme-bounds analysis is performed. This framework was originally proposed by Leamer and Leonard (1981; Leamer, 1983) and employed for business cycle synchronization by Baxter and Kouparitas (2004) and more recently by Böwer and Guillemineau (2006). In the set of first (I) variables – standard gravity variables are used. For estimation purposes, cross section OLS is employed with Newey-West correction for autocorrelation and heteroskedasticity in residuals.

Estimation results have proven structural similarities to be a robust determinant of business cycle synchronization across different levels of disaggregation and for value added and employment shares. On the other hand, the results are not robust across measures – linear measures of specialization yield fragile results. Among other findings, convergence seems to have a strong impact on the economic specialization explanatory power of business cycle synchronization. This finding seems to support Imbs and Wacziarg's U-shaped relationship between specialization and GDP *per capita*, which has been confirmed by Koren and Tenreyro (2007), and by Parteka (2009).

The remainder of the paper is organized as follows: section two provides a literature review; section three provides information about the data and methodology employed; in section four estimation results are presented and section five concludes.

2. Literature Review

Most of the literature concerning business cycle synchronization is based in the theory of optimum currency areas. In their seminal work, Mundell (1961), McKinnon (1963) and Kenen (1969) have established basic criteria that countries need to meet before adopting a common currency (or fixed peg) becomes an optimal solution for them. These criteria were a high degree of labour force mobility and trade openness covering the fiscal and monetary domain and the diversification of the production (and consumption) structure. All these criteria should make the distribution of economic shocks more symmetrical either ex post or ex ante to its occurrence, and the loss of independent monetary policy and flexible exchange rate abolition less costly. Criteria proposed by those authors have been static in their nature – meeting the criteria meant that for a given country, at a given point in time it was optimal to adopt a common currency with another country.

On the other hand, the development of economic theory, especially the concept of the natural rate of unemployment by Friedman (1968) and Phelps (1967) as well as the influence of rational expectations theory on monetary policy effectiveness (Lucas, 1972) led to the creation of the "new" theory of optimum currency areas and a more dynamic approach to integration processes within monetary union (Tavlas, 1993). This literature has brought about two contradicting views on monetary union performance over time. The first is known as "The European Commission View" and states that the more advanced the economic integration, the lower the probability of asymmetric economic shocks, and they are also expected to be less frequent and less intensive (European Economy, 1990). This effect is explained by an increased share of intra-industry trade, which leads to a more symmetrical distribution of economic shocks (Horvath and Komarek, 2002). "The European Commission View" is connected to the hypothesis of the endogeneity of the optimum currency areas criteria proposed by Frankel and Rose (1996). According to their observations, a progress in economic integration leads to higher business cycle correlation through a more symmetrical distribution of demand shocks and an increase in intra-industry trade. This, in consequence, means that optimum currency area criteria can be fulfilled ex post. Lee and Azali (2009) came to similar conclusions based on their research on East Asian countries. Silvestre, Mendonça and Passos (2007), on the other hand, found out that the increases of international trade intensity have a decreasing marginal effect on business cycle synchronization.

The second voice considering the dynamic approach to common currency area performance is known as "The Krugman View". Krugman (1993) argues that in integrating economies, the following four phenomena will occur: regional specialization, instability of regional exports, pro-cyclical capital flows and divergence of long-run growth. Bayoumi and Eichengreen argue that the United States, as a common currency area, are characterized by higher specialization and higher intensity of asymmetric demand shocks when compared to the less integrated European Union (1992).

Due to the fact that economic shocks are unobservable, most of the recent literature focuses attention on verifying hypotheses about different determinants of business cycle synchronization. Imbs (2003) finds a significant and positive relationship between business cycle synchronization and specialization, capital mobility and trade using a system of simultaneous equations. The same approach with the same results has been provided more recently by Siedschlag (2010) and Dées and Zorell (2011). Kalemli-Ozcan, Papaioannou and Peydro (2009), in contrast with Imbs, find that financial integration influences business cycle synchronization negatively. They argue that a cross-section analysis suggests the positive impact of financial integration on business cycle synchronization, but the panel approach reveals the opposite effect. Baxter and Koutraparitsas (2004) employ extreme bounds analysis to several potential determinants of business cycle synchronization, but beside the gravity variables they found only trade to be significant. In a more recent approach, Böwer and Guillemineau (2006) using the same methodology but focusing their attention on the Euro Area, found only trade, economic specialization at industry level, fiscal deficits, price competitiveness and stock market differentials to be significant business cycle synchronization determinants. In yet another attempt to use extreme bounds analysis, Sachs and Schleer (2013) obtained significant results for institutional similarities and directions of structural reforms, but find trade, structural similarities and fiscal and monetary policy similarities insignificant in many of their specifications. On the other hand, Bordo and Helbling (2010) argue that increasing business cycle synchronization is a worldwide phenomenon. Lehwald (2012), using the Bayesian dynamic factor model, argues that a great part of the increased business cycle synchronization among euro area countries comes from worldwide tendencies rather than on-going integration.

3. Data and Methodology

This section provides information on data and methodology. Due to problems with data availability (mostly on economic structure), a subset of 20 European countries has been used. The countries included in the sample are: Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Luxemburg, Malta, Netherlands, Poland, Portugal, Slovakia, Spain, Sweden and the United Kingdom. Even though this group does not constitute the full European Union, it will be referred to as the European Union later in the text. All measures used in the analysis are bilateral which for 20 countries yield 190 pairs. Most of the data covers the period between 1990 and 2007 with exceptions mentioned later on, in the text and in Table 1.

Table 1. Data Sources

Variable	Source	Period	Exceptions
bp, ubp	Penn World Table	1987-2010	-
kor1v, ksi1v, kor2v, ksi2v, kor3v, ksi3v	EU KLEMS	1990-2007	Cyprus 1995-2007; Hungary 1995-2007; Malta 1995-2006; Poland 1995-2006; Portugal 1990-2006; Slovakia 1995-2007
kor1e, ksi1e, kor2e, ksi2e, kor3e, ksi3e	EU KLEMS	1990-2008	Cyprus 1995-2007; Hungary 1992-2007; Malta 1994-2006; Poland 1995-2007; Portugal 1990-2006; Slovakia 1995-2007
x	IMF Directions of Trade	1990-2007	-
bd, pd	Eurostat	1995-2007	-
i1, i2, ic, dif, pp	Penn World Table	1990-2007	-
d	Google Maps	-	-

Source: Author´s arrangement

The analysis stops in 2007 for two reasons. Firstly, the data on economic structure at the 2 digit level ends at this year for all European Union countries. Secondly, the Baxter-King band pass filter requires the usage of lags and leads, which makes operations on current data impossible. Alternative measures, the like Hodrick-Prescott (Hodric and Prescott, 1997) filter allows this, but the results at the beginning and the end of the time series become less and less accurate. The data, measures and estimation strategy are presented and described in the next two subsections.

3.1 Data and Measurement

In the next subsection, the rationale for the division of variables into groups are provided. Specific information about the measures and data sources used is presented below.

3.1.1. Dependent Variable

In order to measure business cycle synchronization, annual real GDP time series have been used. Firstly, to extract the cyclical component of GDP the Baxter-King band pass filter is used. The Baxter and King (1999) filter retains both high and low frequency components of the time series, so components of GDP that cannot be influenced by monetary policy. This means the results obtained with this filter are even more useful in the context of optimum currency area theory. The filter is set with k=3 lags and leads and retains all components between 8 and 32 quarters, so p=2 and q=8 for annual data usage. After filtration, values of cyclical components are divided by trend components for each consecutive year, in order to obtain a relative measure (y_i^t). The bilateral correlation coefficient for 1990–2007 for each country pair is then calculated as follows: 35

$$bp_{ij} = cor(y_i^{t,} y_j^t)\ , \tag{1}$$

where i and j denote countries and t denotes time. The measure takes values from -1 to 1, where 1 means perfect synchronization of business cycles. The data for real GDP time series comes from the Penn World Table and covers the period 1987–2010. The usage of a correlation coefficient is economically justified because the degree of co-movement of business cycles determines common monetary policy effectiveness.

3.1.2. *Z* Variables

In the proposed model, Z variables are measures of structural similarities. The first measure is the average value of the correlation coefficient of value added between the pair of countries i and j:

$$kor_{ij}v = \frac{1}{T}\sum_{i=1}^{T} \frac{cov(v_{it}^{\ l}, v_{jt}^{\ l})}{s(v_{it}^{\ l}) * s(v_{jt}^{\ l})}\ , \tag{2}$$

where: $v_{it}^{\ l}$ is value added in sector l as a percentage of total value added in country i, at year t; $v_{jt}^{\ l}$ is value added for sector l as a percentage of total value in country j, at year t; cov is the covariance and s denotes standard deviation. The same measure is then used for shares of total employment (e). The measure takes values form -1 to 1, where one indicates perfect structural similarity.

The second measure proposed is an average value of the pairwise Krugman Specialization Index:

$$ksi_{ij}v = \frac{1}{T}\sum_{i=1}^{T}\sum_{l}^{L}\left|v_{it}^{\,l}, v_{jt}^{\,l}\right| \quad , \tag{3}$$

where L is the number of sectors in the economy. The same measure is then used for employment shares. The measure takes values from 0 to 2, where two indicates no structural similarities at all. To better capture differences in sectoral shares, all measures use three different levels of disaggregation. The division into primary, secondary and tertiary sector is denoted by l, the division into one digit sectors (represented by capital letters) is denoted by 2, and into two digit sectors by 3[1]. Details of the disaggregation into sectors can be found in the appendix. All the data for measures of sectoral similarities come from the EU KLEMS database and covers the period between 1990–2007 with exceptions mentioned in Table 1. Whenever there was data missing, a shorter average has been calculated.

3.1.3. *M* Variables

The first of the M variables is a measure of the intensity of bilateral trade. In order to measure the impact of international trade on business cycle synchronization, values of international trade as a percentage of GDP for each pair of countries for every year t are calculated, and then mean values are used. The measure is defined as:

$$x_{ij} = \frac{1}{T}\sum_{i=1}^{T}\frac{Imports_{ijt} + Exports_{ijt}}{GDP_{it} + GDP_{jt}} \quad , \tag{4}$$

The higher the value of the measure, the higher the trade intensity between countries i and j. Times series for bilateral trade are taken from IMF Directions of Trade.

To capture the impact of international agreements on business cycle synchronization, two dummy variables are used – the first to capture the impact of participation in the European Union, and the second to capture the impact of participation in the monetary union. Of course, being part of the Euro Area means participation in the European Union so usage of both measures might cause multicolinearity problems. On the other hand, those two measures capture different aspects of the economic conditions in the European Union. The first variable defined as eu_{ij} is measured as follows. If both countries are European Union members in a given year then the measure takes the value 1; if at least one of them is not a European Union member measure takes the value 0. Then eu_{ij} is measured as an average for the period between 1990 and 2007. So the measure takes values from the interval [0,1]. This variable should capture the impact of decreased impediments on trade and capital mobility. The second measure mu_{ij} is defined in the same way but measures whether two countries were Euro Area participants. Beside the properties of eu_{ij}, mu_{ij} should capture the impact of the eliminated exchange rate risk and common monetary policy.

To capture the impact of differences in fiscal policy, two additional measures are introduced. The first measures the correlation of budget deficits as a percentage of GDP for each pair of European Union countries over the period 1995 to 2007. The measure is defined as:

[1] So for example kor2e means: an average value of bilateral correlation coefficient of employment shares at two digit level over period of 1990-2007.

$$bd_{ij} = cor(def_i^t, def_j^t) , \tag{5}$$

where def_i^t is the budget deficit as a percentage of GDP of country *i* at time *t*, and def_{jt} is budget deficit as a percentage of GDP of country *j* at time *t*. The expected sign of the measure depends on the nature of economic shocks. If symmetrical shocks dominate, higher fiscal policy similarities will be associated with higher business synchronization. If asymmetrical shocks dominate, higher fiscal policy similarities will be associated with lower business synchronization. The same argument is true for the measure of fiscal policy similarities employing public debt correlations, as well as for measures of monetary policy similarities presented below.

The second measures the average correlation of public debts as a percentage of GDP between pairs of European Union countries over the period 1995 to 2007. The measure is defined as:

$$pd_{ij} = cor(debt_i^t, debt_j^t) , \tag{6}$$

where $debt_i^t$ is public debt as a percentage of GDP for country *i* at time *t*, and $debt_j^t$ is public debt as a percentage of GDP for country *j* at time *t*. Measures take values between -1 and 1, where 1 indicates perfect correlation of fiscal policy between the two countries. One of the problems associated with these measures is the fact that one cannot tell whether they cause asymmetric shocks or rather are the effects of them. Because these measures are *M* variables, this does not seem to be too much of a problem. To calculate these measures, time series from Eurostat have been used.

To measure differences in monetary policy as a proxy, a correlation coefficient of inflation rates between country i and j over the period 1990 to 2007 is used. The measure is defined as:

$$i_{ij} = cor(i_i^t, i_j^t) , \tag{7}$$

The interpretation and value interval for i_{ij} is the same as in the case of bd_{ij} and pd_{ij}. Assuming that the central banks in European Union countries follow inflation targets, this measure should be a good proxy. On the other hand, differences in inflation rates might reflect effects of asymmetrical economic shocks, which would suggest problems with endogeneity. As in the case of fiscal policy measures, this should not be too much of a problem, because i_{ij} is an *M* variable. For robustness purposes, three different measures of inflation are used: $i1_{ij}$, $i2_{ij}$ and ic_{ij}. *i1* is measured using the G-K method, *i2* is an average for GEEK-CPDW, and *ic* for the consumer price index. Data for i_{ij} has been obtained from Penn World Table.

To capture global tendencies in the world economy that might affect business cycle synchronization among European Union countries, another proxy is established. To calculate this, first the Baxter-King band pass filter with k=3, p=2 and q=8 is applied to US annual real GDP time series for the period between 1987 and 2010. Then, the cyclical component of GDP is divided by the trend value to obtain the relative measure yust. As a result, a time series for 1990–2007 is obtained, just as the one calculated for European Union countries before. Then the correlation coefficient with all countries from the analysed sample for 1990–2007 is calculated as:

$$bpu_i = cor(y_i^t, y_{US}^t) , \tag{8}$$

Finally, the bilateral sum of those measures can be used to capture how changes in business cycle synchronization with the USA influence business cycle synchronization among European Union countries. The measure takes the form of:

$$ubp_{ij} = bpu_i + bpu_j \ , \qquad (9)$$

The data for this measure has been taken from the Penn World Table. The last M variable captures the level (degree) of real GDP *per capita* convergence among the European Union countries (in other words real GDP *per capita* distance). It is measured as the 1990–2007 mean of the absolute value of differences of natural logarithms of the two countries' real GDP *per capita*:

$$dif_{ij} = \frac{1}{T}\sum_{i=1}^{T} mod[\ln(GDPper\,capita_{it}) - \ln(GDPper\,capita_{jt})] \ , \qquad (10)$$

The data for GDP *per capita* comes from the Penn World Table.

3.1.4. *I* Variables

The set of *I* variables is made of four standard gravity variables. The first of them is an average value of bilateral population product between the two European Union member countries over the period 1990–2007:

$$pp_{ij} = \frac{1}{T}\sum_{i=1}^{T} pop_{it}\ pop_{jt} \ , \qquad (11)$$

where pop_{it} and pop_{jt} are populations of country *i* and *j* at time *t* respectively. The data for pp_{ij} comes from the Penn World Table.

The second *I* variable is denoted by d_{ij} and represents the shortest way between the capitals of any two sample countries according to Google Maps. The last two variables are dummy variables – b_{ij} denotes a common border and l_{ij} denotes a common language – at least one of the officially used languages.

3.2. Estimation Strategy

To identify to what extent structural similarities determine business cycle synchronization in the European Union, extreme bounds analysis (EBA) is employed. This method was originally proposed by Leamer and Leonard (1981, Leamer, 1983, 1985) and its extensions were developed by Levine and Renelt (1992) and Sala-i-Martin (1997a, 1997b). EBA has been employed to analyse business cycle synchronization by Baxter and Kouparitas (2004) and more recently by Böwer and Guillemineau (2006), as well as Sachs and Schleer (2013).

The sample consists of 190 pairs of European Union countries. OLS with Newey-West correction for heteroskedasticity residuals is employed to estimate an equation of the form:

$$bp = \alpha_k + \beta_{zk} Z + \beta_{mk} M + \beta_{ok} I + \varepsilon \ , \qquad (12)$$

where *bp* is a vector of cyclical components of output correlation coefficients, Z is a vector of variable of interest (measure of structure similarities), M is a matrix of up to three variables that have proven to be robust determinants of business cycle synchronization in past literature and I is a matrix of always included variables. Then, for each model k, one finds β_{zk} and the corresponding standard error σ_{zk}. After finding the lowest value of $\beta_{zk} - \beta_{zk}^{min}$ the lower extreme bound can be defined as:

$$\beta_l = \beta_{zk}^{min} - 2\sigma_{zk} \ , \tag{13}$$

After finding the highest value of $\beta_{zk} - \beta_{zk}^{max}$ the upper extreme bound can be defined as:

$$\beta_u = \beta_{zk}^{max} + 2\sigma_{zk} \ , \tag{14}$$

If both extreme bounds have the same sign and the Z variable is significant across all models, the result is qualified as robust. As Sala-i-Martin (1997) pointed out, this test is too extreme because if the Z variable is not significant or its sign changes in just one regression, the test marks the variable as fragile. No wonder that Baxter and Kouparitas (2004) as well as Böwer and Guillemineau (2006) found that specialization and structural similarities of two economies as determinants of business cycle synchronization were fragile. This is why Sala-i-Martin proposes not to look only at extreme values but rather at the whole distribution of estimated coefficients across all models. In that case, one would only be interested in the fraction of coefficients that lay either above or below zero. Then if 90 per cent or more of the coefficient lie above/below zero, one might qualify the variable as robust. But as the distribution of the estimates is unknown, two assumptions are required.

The first states that the distribution of the estimates across models is normal. In that case for each of the K models β_{zk}, σ_{zk} is calculated along with integrated likelihoods – lh_{zk}. Using these values, the mean point estimate can be calculated as:

$$\beta_{za} = \frac{1}{K}\sum_{k=1}^{K} \beta_{zk} \ , \tag{15}$$

and the mean standard deviation as:

$$\sigma_{za} = \frac{1}{K}\sum_{k=1}^{K} \sigma_{zk} \ , \tag{16}$$

Also, the weighted mean point estimate can be estimated as:

$$\beta_{zw} = \sum_{k=1}^{K} w_{zk} \ \ \beta_{zk} \ , \tag{17}$$

and the mean weighted standard deviation:

$$\sigma_{zw} = \sum_{k=1}^{K} w_{zk} \ \ \sigma_{zk} \ , \tag{18}$$

where:

$$w_{zk} = \frac{lh_{zk}}{\Sigma^{K}_{k=1} \, lh_{zk}} \ . \tag{19}$$

The reason for using likelihoods is to give more weight to models that are referred to by Sala-i-Martin as "true regression models". Knowing the values of the means and standard errors, the value of the first average cumulative distribution function for zero can be computed as:

$$CDF_{a1} = \Phi(0\backslash\beta_{za},\sigma_{za}) \ , \tag{20}$$

and the value of the normal cumulative distribution function of weighted averages for zero as:

$$CDF_{n} = \Phi(0\backslash\beta_{zw},\sigma_{zw}) \ , \tag{21}$$

If the portion of coefficients with the same sign is equal to or exceeds 0.9, we can say that the results are robust under the assumption of normal distribution.

The situation changes with the assumption that the distribution of the estimates across models is not normal. Here the weighted average of individual cumulated distribution functions is required to be calculated as:

$$CDF_{w} = \sum_{k=1}^{K} w_{zk}\,\Phi_{zk}(0\backslash\beta_{zk},\sigma_{zk}) \ . \tag{22}$$

If some explanatory variables are endogenous, models using them might have a better fit, so the corresponding weights are going to be larger. To prevent this problem, the value of the second average cumulative distribution function for zero is also calculated. The measure is defined as:

$$CDF_{a2} = \frac{1}{K}\sum_{k=1}^{K} \Phi_{zk}(0\backslash\beta_{zwk},\sigma_{zwk}) \ . \tag{23}$$

If the portion of coefficients with the same sign is equal to or exceeds 0.9, we can say that the results are robust under the assumption of not normal distribution.

Finally, while estimating, the following approach will be employed. Firstly, only models with a *Z* variable and each of the *M* variables in company of only I variables are estimated. All of the variables that will be statistically significant, can enter the full EBA procedure. Then, regressions with a *Z* variable, I variables and one of each of *M* variables are computed. The procedure is then repeated for all sets of two *M* variables and each set of three *M* variables. Of course, some of the *M* variables measure the same determinants, that is why one additional restriction must be imposed to avoid multicolinearity. In any of the estimated equations there cannot be variable *bd* and *pd* as well as *i1, i2* and ic at the same time.

The result will be reported for equations with one, two and three *M* variables as well as for all of those combinations with the addition of models with no *M* variables. If all models of interest pass the EBA test, the results are denoted as EBA robust. If all models pass only the criteria proposed by Sala-i-Martin, the result is denoted as SiM robust. If all models pass only the Sala-i-Martin criteria for normal distribution, result is denoted as N robust. And if, by any chance, all models pass only the Sala-i-Martin criteria for not normal distribution, the result is denoted as NN robust. In any other case, the results are considered fragile.

After obtaining all the results, fragility to conditioning set of information will be further explored. Average and weighted (with integrated likelihood) values of the *t*-statistic for each *Z* variable will be calculated for each of the models with a given *M* variable. This procedure helps determine which *M* variables are associated with the highest and which with the lowest values of the *Z* variable *t*-statistic. This in turn can determine whether the insignificance of one of the *Z* variables is a result of the impact of one particular variable or a specific combination of *M* variables. Separate calculations will be made for the number of *M* variables.

4. Estimation Results

In the first step, estimations with only *I* variables are computed. Their results are presented in Table 2.

Table 2. Primary Estimation Results*

Variable	*kor1e*	*kor1v*	*ksi1v*	*ksi1e*	*kor2v*	*kor2e*	*ksi2v*	*ksi2e*	*kor3v*	*kor3e*	*ksi3v*
β	1.56	1.48	-0.30	-0.11	1.17	1.18	0.26	0.24	1.14	1.12	0.28
Se	0.12	0.12	0.32	0.23	0.11	0.13	0.23	0.23	0.11	0.11	0.28
t	13.40	12.01	-0.94	-0.49	10.31	8.92	1.15	1.02	10.28	10.65	1.02
Adj. R^2	0.49	0.53	0.02	0.02	0.41	0.37	0.02	0.02	0.38	0.45	0.02
Variable	ksi3e	x	mu	eu	bd	pd	i1	i2	ic	ubp	dif
β	-0.14	23.29	0.66	0.64	0.43	0.09	0.82	0.82	0.78	0.28	-0.49
Se	0.40	5.40	0.08	0.05	0.05	0.04	0.06	0.06	0.06	0.09	0.06
t	-0.34	4.31	8.46	13.41	7.95	2.55	12.81	12.76	12.67	3.11	-8.62
Adj. R^2	0.02	0.16	0.29	0.53	0.26	0.04	0.44	0.44	0.44	0.05	0.35

Note: *All estimations computed using OLS with Newey-West correction for heteroskedasticity in residuals
Source: Author´s calculations

Looking at the *Z* variables provides a very clear-cut distinction – in all equations with correlation coefficient point estimate is significant at 0.01 level and of the expected sign. On the other hand, in all equations with Krugman Specialization Index, point estimates are not significant, even at 0.1 level and are of an opposite sign in the case of *ksi2v, ksi2e* and *ksi3v*. One possible explanation can be found in Table 3 and Figure 1.

The Krugman Specialization Index is a linear measure, so it puts the same weight on all the differences between the sectoral shares in the analysed countries. On the other hand, the correlation coefficient[2] involves squares of differences between shares and average values, so it puts more weight on the small differences. This might explain why the values of the standard deviations are constantly higher for correlation coefficients across all levels of disaggregation and for both value added and employment. Also, standard deviation increases with increasing disaggregation for the correlation coefficient and remains relatively stable for the Krugman Specialization Index. This effect can be seen as especially strong for 2 digit level of disaggregation when one looks at the *p* value for the Jarque–Berra statistics – *kis3v* exhibits almost normal distribution and *ksi3e* is characterized by normal distribution.

[2] Even though correlation coefficient is a linear measure it uses squares of differences in structural shares and by this puts more weight on 'small' differences than Krugman Specialization Index.

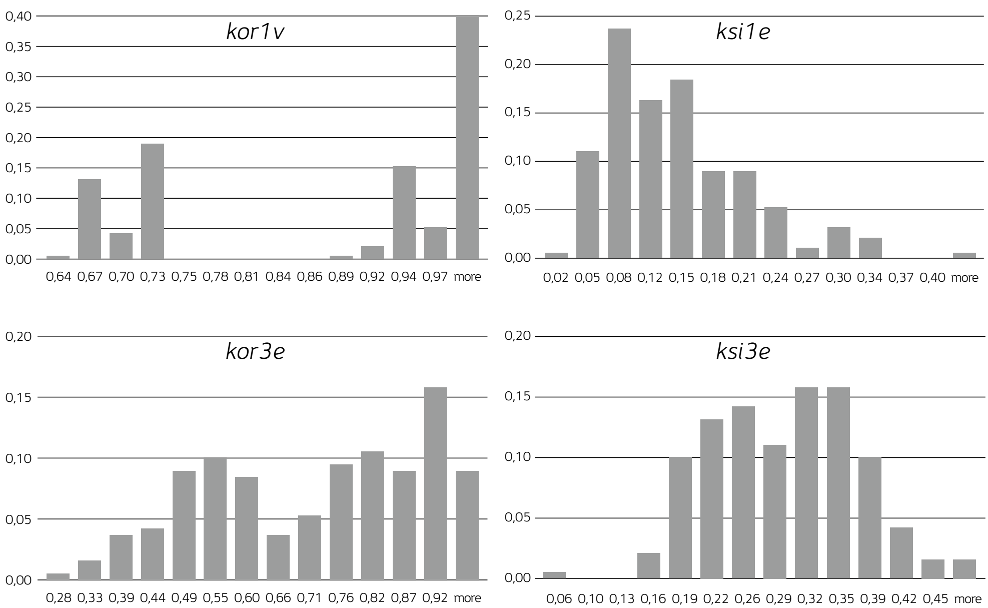
Table 3. Descriptive Statistics for the Dependent Variable and Z Variables

	bp	*kor1v*	*ksi1v*	*kor1e*	*ksi1e*	*kor2v*	*ksi2v*	*kor2e*	*ksi2e*	*kor3v*	*ksi3v*	*kor3e*	*ksi3e*
Mean	0.49	0.87	0.13	0.86	0.15	0.76	0.27	0.73	0.30	0.70	0.33	0.69	0.28
Median	0.55	0.94	0.11	0.88	0.13	0.82	0.25	0.74	0.30	0.72	0.32	0.73	0.28
Max	0.91	1.00	0.43	1.00	0.51	0.98	0.51	0.98	0.52	0.96	0.62	0.98	0.48
Min	-0.25	0.64	0.02	0.61	0.02	0.32	0.14	0.35	0.13	0.32	0.07	0.28	0.06
Std. Dev.	0.30	0.14	0.07	0.13	0.10	0.17	0.08	0.16	0.09	0.17	0.09	0.19	0.07
Skewness	0.64	-0.52	1.11	-0.35	1.16	-0.38	0.76	-0.29	0.32	-0.17	0.34	-0.31	0.08
Kurtosis	2.32	1.42	4.28	1.55	4.40	1.92	2.99	1.94	2.48	1.84	2.61	1.82	2.61
p(JB)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.00	0.09	0.00	0.50

Source: Author´s calculations

The same thing cannot be said about the correlation coefficient. Just by looking at Figure 1, one might realize that the values of the Krugman Specialization Index are concentrating around the mean, which is clearly not the case for the correlation coefficient. This might indicate that business cycle synchronization is very sensitive to even very small differences among shares between sectors. This conclusion would also explain why Böwer and Guillemineau and Sachs and Scheleer were not able to obtain significant results as they were using a linear measure. A similar problem with using linear measures has been reported by Kalemli-Ozcan, Sørensen and Yosha (2002) in their analysis of the impact of specialization on risk sharing.

Figure 1. Density Histograms for *kor1v, ksi1v, kor3e* and *ksi3e*



Source: Author´s calculations

All M variables are proven to be statistically significant and of the expected sign. The most interesting case here seems to be the negative sign for real GDP *per capita* convergence. This sign might be explained by Imbs and Wacziarg (2003) concept of the U-shaped relationship between GDP *per capita* and specialization. Most of the European Union countries are developed countries, and the rest is in a process of catching up. The negative sign for the point estimate for *dif* might come from the fact that higher convergence leads to higher GDP *per capita* in catching up countries and through this to lower specialization. Then, lower specialization might lead to higher business cycle synchronization among European Union countries.

After eliminating the Krugman Specialization Index, as a candidate for *Z* variables, there are only six remaining: *kor1v, kor1e, kor2v, kor2e, kor3v* and *kor3e*. Because all *M* variables have passed the first step in EBA, there will be 10 equations estimated for one *M* variable case, 41 for sets of two *M* variables and 90 for sets of three *M* variables. All in all it yields a sum of 142 equations for each *Z* variable (including one with no *M* variables). The results of the estimations are presented in Table 4.

Table 4. EBA Estimation Results for *kor1v, kor1e, kor2v, kor2e, kor3v* and *kor3e* (Dependent Variable *bp*)

Z	E	βu	βl	βa	σa	Bw	σw	CDFa1	CDFn	CDFa2	CDFw	k	Robustness
kor1v	1	1.75	0.08	1.15	0.14	1.10	0.14	1.000	1.000	0.999	0.999	10	EBA robust
	2	1.76	-0.36	0.84	0.16	0.78	0.17	1.000	1.000	0.981	0.969	41	SiM robust
	3	1.63	-0.74	0.55	0.18	0.50	0.19	0.999	0.996	0.895	0.871	90	N robust
	All	1.76	-0.74	0.68	0.17	0.61	0.18	1.000	1.000	0.926	0.904	142	SiM robust
kor1e	1	1.88	0.37	1.26	0.13	1.24	0.12	1.000	1.000	1.000	1.000	10	EBA robust
	2	1.87	-0.01	1.00	0.14	0.97	0.14	1.000	1.000	0.999	0.998	41	SiM robust
	3	1.75	-0.63	0.73	0.16	0.70	0.16	1.000	1.000	0.966	0.960	90	SiM robust
	All	1.88	-0.63	0.85	0.15	0.81	0.15	1.000	1.000	0.978	0.973	142	SiM robust
kor2v	1	1.43	0.24	0.88	0.12	0.79	0.11	1.000	1.000	1.000	1.000	10	EBA robust
	2	1.44	-0.08	0.65	0.13	0.58	0.13	1.000	1.000	0.998	0.997	41	SiM robust
	3	1.35	-0.15	0.46	0.14	0.42	0.14	1.000	0.999	0.981	0.977	90	SiM robust
	All	1.44	-0.15	0.55	0.13	0.48	0.13	1.000	1.000	0.987	0.983	142	SiM robust
kor2e	1	1.45	0.05	0.84	0.13	0.72	0.12	1.000	1.000	0.999	0.998	10	EBA robust
	2	1.44	-0.27	0.57	0.13	0.49	0.12	1.000	1.000	0.987	0.976	41	SiM robust
	3	1.32	-0.36	0.35	0.13	0.30	0.13	0.996	0.990	0.920	0.901	90	SiM robust
	All	1.45	-0.36	0.45	0.13	0.37	0.13	1.000	0.998	0.944	0.924	142	SiM robust
kor3v	1	1.39	0.16	0.82	0.12	0.71	0.12	1.000	1.000	1.000	1.000	10	EBA robust
	2	1.37	-0.09	0.58	0.13	0.50	0.12	1.000	1.000	0.996	0.993	41	SiM robust
	3	1.25	-0.19	0.39	0.13	0.35	0.13	0.999	0.997	0.967	0.959	90	SiM robust
	All	1.39	-0.19	0.48	0.13	0.40	0.13	1.000	0.999	0.978	0.969	142	SiM robust
kor3e	1	1.40	0.03	0.87	0.10	0.81	0.10	1.000	1.000	0.999	0.999	10	EBA robust
	2	1.40	-0.33	0.67	0.11	0.63	0.11	1.000	1.000	0.986	0.981	41	SiM robust
	3	1.32	-0.54	0.49	0.12	0.47	0.12	1.000	1.000	0.947	0.947	90	SiM robust
	All	1.40	-0.54	0.57	0.12	0.53	0.12	1.000	1.000	0.961	0.959	142	SiM robust

Note: *E* denotes number of *M* variables in the set
Source: Own calculations

The EBA test for robustness was passed by all *Z* variables only for sets with one *M* variable. In all other cases the lower band moved below zero. The results are SiM robust for *kor1e, kor2v, kor2e, kor3v* and *kor3e*, and only robust for kor1v but only under the assumption of the normal distribution of point estimates. This makes a very strong case for structural similarities as a robust determinant of business cycle synchronization in the European Union. The case is especially strong because the results are proven to be robust across different levels of disaggregation and for both shares of value added and employment.

The average and weighted values of coefficients are significantly higher for the lowest level of disaggregation on the one hand, and do not differ a lot between the other two levels of disaggregation. This might indicate that for high aggregates the responsiveness of business cycle synchronization is strong and becomes lower with disaggregation, but after reaching some point, disaggregation does not seem to matter. This conclusion might be important for future research because two digit level data is very difficult to obtain. Differences between point estimate measures using value added and employment do not exhibit any significant pattern. Another reason for the high value of average and weighted point estimates for the highest level of disaggregation is the fact that countries with development converge to state with low shares of primary and secondary sectors and a high share of tertiary sector. In this context, similarities at the lowest level of disaggregation might proxy for other factors like, for example, stage of development.

Table 5. EBA Estimation Results for *ubp* and *dif* (Dependent Variable *bp*)

Z	E	βu	βl	βa	Σa	Bw	σw	CDFa1	CDFn	CDFa2	CDFw	k	Robustness
dif	1	-0.12	-0.60	-0.32	0.06	-0.28	0.05	1.000	1.000	1.000	1.000	15	EBA robust
	2	0.01	-0.60	-0.24	0.06	-0.22	0.05	1.000	1.000	0.997	0.996	86	SiM robust
	3	0.03	-0.55	-0.20	0.05	-0.19	0.05	1.000	1.000	0.994	0.994	250	SiM robust
	All	0.03	-0.61	-0.21	0.06	-0.20	0.05	1.000	1.000	0.995	0.994	352	SiM robust
ubp	1	0.61	-0.29	0.14	0.08	0.10	0.14	0.958	0.773	0.568	0.922	15	Fragile
	2	0.62	-0.30	0.13	0.12	0.14	0.15	0.856	0.815	0.775	0.831	86	Fragile
	3	0.52	-0.30	0.15	0.08	0.16	0.08	0.975	0.984	0.883	0.906	250	N robust
	All	0.62	-0.30	0.15	0.09	0.16	0.09	0.951	0.955	0.841	0.894	352	N robust

Note: *E* denotes number of *M* variables in the set
Source: Author´s calculations

To further explore the relationship between business cycle synchronization and structural similarities, EBA is employed to show the degree of convergence (*dif*) and business cycle synchronization with the USA (*ubp*). Because all *M* variables (except Krugman Specialization Index measures) passed the first step in EBA, now there will be 15 equations estimated for one *M* variable cases, 86 for sets of two *M* variables and 250 for sets of three *M* variables. All in all, this yields a sum of 352 equations for each *Z* variable (including one for no *Z* variables). The results of the estimations are presented in Table 5, where we can see that *ubp* has proven to be robust with the assumption of normal distribution of estimates across models only for models with 3 *M* variables and for all models. In models with 1 and 2 *M* variables, the results are fragile. This result supports the notion that *ubp* reveals its impact on business cycle synchronization only when its properly controlled for. In addition, *dif* has proven to be the most robust variable explaining business cycle synchronization with the EBA test almost passed for sets of two and three variables and all coefficients of the expected sign. 1 *M* variable results are EBA robust and 2 and 3 *M* variables are SiM robust, as in the case of all the models. The negative point estimate indicates that lower GDP *per capita* distance leads to higher business cycle synchronization.

In the next step, the problem of whether the significance of the results relies upon including one particular variable is addressed. To achieve that, the average (*at*) and weighted (with integrated likelihood) (*wt*) values of the *t*-statistic of the *Z* variable have been calculated for models containing each of the *M* variables in the set of 1, 2 or 3 *M* variables. Each set of models is also described according to the mean value of the natural logarithm of likelihood (alog) or just the value of the natural logarithm of likelihood (log) in the case of models with *M*=1. The results for *kor1v, kor1e, kor2v, kor2e ,kor3v* and *kor3e* are shown in Table 6. Insignificant values for the *t*-statistic (at the conventional level of 10%) have been highlighted in bold.

The results in Table 6 reveal only one *M* variable that is associated with the low value of the *t*-statistic for *Z* variables. This variable is participation in the European Union (*eu*) and its inclusion makes *kor1v* insignificant in models with 2 or 3 *M* variables, *kor2e, kor3e* and *kor3v* in models with 3 *M* variables. In the case of *kor3v*, results are insignificant only in the weighted scheme. This result might come from the fact that participation in the European Union might also work as a proxy for other factors, like stage of development, volume of trade or unaccounted for institutional differences. The rest of the results reveal that the correlation coefficients of structural shares are significant (and of the correct sign) across all models and all *M* variables with the exception of *eu*. This suggests that insignificant results are associated with specific combinations of *M* variables; this notion will be further explored later on.

The exercise from Table 6 has also been repeated for *ubp* and *dif*. Results are presented in Table 7, and insignificant values for the *t*-statistic (at 10%) have been highlighted in bold. Insignificant values of the *t*-statistic for *ubp* are associated with models that include measures of structural similarities (at different levels of disaggregation and for value added and employment shares), fiscal policy similarities and the logarithm for the GDP *per capita* distance. Although the *Z* variable is insignificant in most models with 1 (for measures of structural similarities and *bd*) and 2 *M* variables, what confirms that impact of synchronization with the USA is significant only when it is properly controlled for. Significant values for the *t*-statistic for *ubp* are associated with models controlling for monetary/European Union participation and monetary policy similarities. The degree of real GDP *per capita* convergence (*dif*) is reported as significant across all model sizes and *M* variables. This is yet more proof that convergence is a robust determinant of business cycle synchronization. What is more, the logarithm of GDP *per capita* distance is the most robust of all determinants analysed in this paper.

Table 6. Significance of Obtained Results for *kor1v, kor1e, kor2v, kor2e ,kor3v* and *kor3e* in Different Model sets

Variable		M=1			M=2				M=3					M=1			M=2				M=3			
M	Z	t	log	e	at	wt	alog	e	at	wt	alog	e	Z	t	log	e	at	wt	alog	e	at	wt	alog	e
x		11.2	27.1	1	8.1	7.8	35.4	9	5.06	4.72	41.7	32		12.5	35.5	1	10.0	10.0	42.1	9	6.9	6.8	47.8	32
mu		8.3	30.4	1	5.9	5.7	38.4	9	3.77	3.53	45.2	32		11.0	36.7	1	8.4	8.2	42.1	9	5.5	5.4	49.5	32
eu		2.3	38.3	1	1.5	1.5	44.9	9	0.78	0.66	50.9	32		3.8	41.4	1	2.9	2.9	47.2	9	2.0	1.9	52.4	32
bd		7.8	24.3	1	4.9	4.5	35.7	8	3.02	2.69	43.6	25		9.9	32.4	1	7.0	6.7	41.8	8	4.8	4.6	48.4	25
pd	kor1v	11.7	23.6	1	7.8	7.4	34.3	8	4.96	4.59	42.9	25	kor1e	13.0	31.2	1	9.6	9.5	40.4	8	6.7	6.5	47.3	25
i1		8.3	37.8	1	5.2	5.0	43.5	7	3.06	2.82	49.3	20		10.7	43.9	1	7.1	7.0	48.3	7	4.7	4.5	52.6	20
i2		8.4	38.1	1	5.2	5.0	43.8	7	3.10	2.89	49.8	20		10.7	44.0	1	7.1	7.0	48.4	7	4.7	4.6	52.7	20
ic		8.3	38.5	1	5.3	5.1	44.1	7	3.22	3.00	49.7	20		10.8	44.2	1	7.3	7.2	48.4	7	4.8	4.7	52.9	20
ubp		11.9	23.5	1	7.7	7.3	33.4	9	4.44	4.03	43.2	32		13.2	32.4	1	9.0	8.8	39.5	9	5.6	5.3	46.9	32
dif		8.3	36.8	1	6.3	6.1	42.5	9	4.33	4.08	47.3	32		9.8	41.4	1	8.3	8.2	45.2	9	5.9	5.8	51.3	32
x		9.1	14.3	1	6.7	6.3	28.5	9	4.40	4.40	39.7	32		7.7	10.3	1	6.0	5.7	25.2	9	3.9	3.5	36.5	32
mu		8.2	28.5	1	6.2	6.0	39.8	9	4.16	3.98	46.4	32		6.7	17.2	1	4.7	4.5	30.6	9	2.9	2.7	41.1	32
eu		3.9	41.8	1	3.0	3.0	47.7	9	2.18	2.12	52.7	32		2.3	37.2	1	1.7	1.7	44.4	9	1.1	1.0	49.9	32
bd		6.9	16.2	1	4.7	4.3	32.5	8	3.24	3.03	43.1	25		6.2	11.6	1	4.2	3.9	29.0	8	2.6	2.4	40.6	25
pd	kor2v	10.2	12.9	1	6.8	6.2	29.2	8	4.46	4.12	40.5	25	kor2e	9.0	6.8	1	6.3	5.8	24.9	8	3.9	3.5	37.5	25
i1		7.3	37.7	1	4.9	4.7	43.7	7	3.20	3.08	49.4	20		7.8	35.6	1	4.9	4.7	41.8	7	2.9	2.6	47.8	20
i2		7.3	37.9	1	4.9	4.8	43.9	7	3.23	3.10	49.6	20		7.8	35.6	1	4.8	4.6	41.8	7	2.8	2.6	47.8	20
ic		7.3	38.0	1	4.9	4.8	44.0	7	3.31	3.18	49.7	20		7.7	35.2	1	4.8	4.6	41.5	7	2.8	2.6	47.6	20
ubp		10.7	12.7	1	6.8	6.3	28.0	9	4.14	3.75	40.4	32		8.7	6.9	1	5.9	5.3	24.2	9	3.4	2.9	38.0	32
dif		4.8	18.9	1	3.6	3.3	31.8	9	2.47	2.24	42.3	32		5.0	16.4	1	3.5	3.2	29.8	9	2.1	1.8	40.8	32
x		9.1	10.4	1	6.1	5.5	25.9	9	3.87	3.54	38.2	32		9.5	20.8	1	7.9	7.8	34.6	9	5.6	5.5	44.4	32
mu		8.2	24.3	1	5.8	5.6	35.6	9	3.83	3.61	44.9	32		8.9	27.4	1	6.9	6.9	39.4	9	4.8	4.7	48.0	32
eu		3.4	38.8	1	2.5	2.4	45.6	9	1.74	1.66	51.4	32		2.2	36.5	1	1.9	2.0	44.8	9	1.5	1.5	51.2	32
bd		6.0	11.4	1	4.0	3.5	29.6	8	2.73	2.47	41.6	25		7.8	19.4	1	5.6	5.3	35.8	8	4.0	3.9	45.8	25
pd	kor3v	9.4	7.1	1	5.9	5.2	26.0	8	3.84	3.45	39.0	25	kor3e	10.7	20.0	1	8.0	7.7	35.4	8	5.6	5.4	45.3	25
i1		6.1	34.4	1	4.0	3.9	41.7	7	2.63	2.52	48.3	20		9.6	49.4	1	6.8	6.7	51.8	7	4.7	4.6	54.7	20
i2		6.1	34.8	1	4.1	3.9	42.0	7	2.70	2.58	48.6	20		9.6	49.7	1	6.8	6.8	52.1	7	4.8	4.7	54.9	20
ic		6.3	35.1	1	4.2	4.1	42.3	7	2.85	2.74	48.8	20		9.7	49.8	1	6.9	6.9	52.2	7	4.9	4.8	55.0	20
ubp		9.9	7.4	1	6.0	5.3	25.5	9	3.64	3.23	39.5	32		11.1	18.7	1	7.6	7.2	33.8	9	4.9	4.6	44.8	32
dif		4.6	17.5	1	3.4	3.1	30.8	9	2.38	2.14	41.8	32		7.5	25.9	1	6.1	6.0	38.3	9	4.4	4.2	47.1	32

Note: *e* denotes number of models associated with a given M variable
Source: Author´s calculations

Table 7. Significance of Obtained Results for *ubp* and *dif* in Different m´Model Sets

Variable		M=1			M=2				M=3			
Z	M	t	log	e	at	wt	alog	e	at	wt	alog	e
ubp	kor1v	-0.28	23.5	1	0.79	0.94	33.4	9	1.73	1.92	43.0	32
	kor1e	-1.48	32.4	1	-0.44	-0.36	39.5	9	0.55	0.68	46.8	32
	kor2v	-0.56	12.7	1	0.73	1.21	26.6	9	1.69	1.96	40.5	32
	kor2e	0.35	6.9	1	1.38	1.82	24.2	9	2.15	2.42	38.0	32
	kor3v	0.79	7.4	1	1.69	2.08	25.5	9	2.31	2.54	39.5	32
	kor3e	-0.50	18.7	1	0.61	0.89	33.8	9	1.42	1.80	44.8	32
	X	2.38	-19.0	1	1.44	1.53	18.1	14	1.56	1.77	36.1	72
	Mu	4.42	6.1	1	3.20	3.40	30.6	14	2.98	3.16	44.1	72
	Eu	2.30	37.1	1	2.08	2.19	44.2	14	2.29	2.41	50.9	72
	Bd	1.43	-8.3	1	1.09	1.41	23.4	13	1.61	1.82	39.6	60
	Pd	2.46	-31.7	1	1.41	1.52	16.9	13	1.65	1.78	36.5	60
	i1	4.36	26.0	1	2.74	2.74	41.2	12	2.57	2.64	49.3	50
	i2	4.33	25.9	1	2.71	2.71	41.3	12	2.54	2.61	49.4	50
	Ic	4.45	25.5	1	2.76	2.76	41.3	12	2.57	2.64	49.5	50
	Dif	1.79	4.4	1	1.37	1.51	27.3	14	1.67	1.85	41.1	72
dif	kor1v	-4.97	36.8	1	-4.67	-4.65	42.5	9	-4.35	-4.34	48.0	32
	kor1e	-4.78	41.4	1	-4.45	-4.44	46.6	9	-4.12	-4.10	51.3	32
	kor2v	-2.89	18.9	1	-2.68	-2.64	31.8	9	-2.59	-2.58	42.3	32
	kor2e	-4.13	16.4	1	-3.75	-3.65	29.8	9	-3.51	-3.44	40.8	32
	kor3v	-3.69	17.5	1	-3.46	-3.44	30.8	9	-3.30	-3.28	41.8	32
	kor3e	-4.13	25.9	1	-3.54	-3.32	38.3	9	-3.19	-3.41	47.1	32
	X	-7.03	6.7	1	-4.83	-4.65	27.0	14	-3.77	-3.71	40.1	72
	Mu	-8.26	29.1	1	-6.02	-5.94	40.2	14	-4.74	-4.65	48.2	72
	Eu	-6.22	46.3	1	-5.18	-5.14	50.0	14	-4.40	-4.32	54.0	72
	Bd	-7.37	13.7	1	-4.80	-4.64	31.5	13	-3.77	-3.69	43.4	60
	Pd	-8.11	3.4	1	-5.09	-4.89	27.7	13	-4.05	-4.03	41.0	60
	i1	-5.43	32.4	1	-3.55	-3.55	44.0	12	-3.06	-3.11	50.6	50
	i2	-5.42	32.3	1	-3.53	-3.53	44.0	12	-3.03	-3.08	50.6	50
	Ic	-5.52	31.6	1	-3.56	-3.55	43.8	12	-3.04	-3.08	50.5	50
	ubp	-8.18	4.4	1	-5.36	-5.23	27.3	14	-4.21	-4.20	41.1	72

Note: *e* denotes number of models associated with a given *M* variable
Source: Author´s calculations

In the next step, the combinations of *M* variables associated with the highest and lowest values of the *t*-statistics have been analysed[3]. In models where *kor2v, kor2e, kor3v* and *kor3e* served as *Z* variables, insignificant values of the *t*-statistic were associated with combinations of *eu* and

[3] List of sets of M variables in order of significance has not been reported for brevity, full list is available upon request.

dif as *M* variables. On the other hand, the lowest values of the *t*-statistic for *kor1v* and *kor1e* are associated solely with the inclusion of *eu*. One interpretation of this result might be that the degree of convergence takes explanatory power away from measures of structural similarities as determinants of business cycle synchronization when *eu* is controlled for. Given that European Union countries are divided into developed and catching up countries, real GDP *per capita* convergence is proceeding mostly through the decreasing distance produced by the catching up countries. In keeping with Imbs and Wacziarg's (2003) U-shaped specialization curve, reaching higher real GDP *per capita* convergence by catching up might lead to lower structural divergence. The fact that around some value of GDP *per capita* specialization pattern changes direction might cause insignificant t-statistic for the point estimate. Convergence does not impact the significance of structural similarities, when the lowest level of disaggregation is taken into consideration because, as described by Imbs and Wacziarg and confirmed by Koren and Tenreyro (2007), and by Parteka (2009), sectoral divergence takes place only at higher disaggregation levels. Also, there is no proof that high values of the *t*-statistic are associated with some particular combinations of *M* variables

Repeating the same exercise for *ubp* shows that the lowest values of the *t*-statistic are associated with the inclusion of measures of structural similarities, and the highest, with the inclusion of monetary union participation. This assumes that the *mu* proxy for ability to risk sharing this result is in keeping with work of Kraay and Ventura (2002) and Kalemli-Ozcan, Sørensen and Yosha (2002). Controlling for mu reveals that two countries that are able to share some of the risk might transmit a larger part of the shocks to one another. In that case, for any two countries, the degree of business cycle synchronization with each other depends more on synchronization with the outside world (here with the USA). The fact that the inclusion of structural similarities also makes the result insignificant suggests that the dependence of the degree of business cycle synchronization between two countries on business cycle synchronization with the outside world is conditional on structural similarities. Two countries with a very similar structure will respond to outside shock similarly because of their similar specialization pattern – *dif* is significant for all the *M* variables used.

To further explore the relationship between real GDP *per capita* distance, structural similarities and business cycle synchronization, the following system of simultaneous equations is estimated using two and three stage least squares:

$$bpi,j = \alpha_1 + \beta_1 korv2v_{i,j} + \beta_3 I_{1,i,j} + \varepsilon_{1,i,j} \ , \tag{24}$$

$$korv3v_{i,j} = \alpha_2 + \beta_2 ln_{i,j} + \beta_4 I_{2,i,j} + \varepsilon_{2,i,j} \ , \tag{25}$$

where imp indexes country pairs and I_1 and I_2 are matrices of instrumental variables. The results of the estimation are presented in Table 8.

In all estimated systems, the logarithm of GDP *per capita* distance has negatively and significantly influenced structural similarities, and structural similarities has significantly and positively influenced business cycle synchronization. Regardless of the set of *M* variables used as instruments, similar results were reached. In other words, if EBA was conducted using changes in the conditional set of instruments, both *kor3v* and *dif* would pass the test. Similar results were also obtained with OLS, OLS with Newly-West correction for heteroskedasticity in residuals, Seemingly Unrelated Regressions, Full and Limited Information

Maximum Likelihood, as well as measures of employment shares used instead of value added shares[4]. The Breusch-Pagan test showed no problem with heteroskedasticity and the Sargan test revealed no problems with over identification.

These results suggest that convergence might inexplicitly – through the channel of specialization – positively influence business cycle synchronization. In addition, in the system used, the value of the point estimate for the measure of structural similarities in equation (24) increases with the level of disaggregation. This once more confirms that *kor1v* and *kor1e* might work as a proxy for stage of development. The impact of the degree of convergence on *kor1v* and *kor1e* is also the smallest compared with other levels of disaggregation, which might reflect the fact that structural similarities at the sector level do not depend much on the real GDP *per capita* distance.

Table 8. Two and Three Stage Least Squares Results for System (24-25)

Two Stages Least Squares												
equation	(24)	(25)	(24)	(25)	(24)	(25)	(24)	(25)	(24)	(25)	(24)	(25)
variable 1	α_1	α_2	α_1	α_2	α_1	α_2	α_1	α_2	α_1	α_2	α_1	α_2
α	-0.24	0.84	-0.58	0.84	-0.50	0.84	-0.55	0.91	-0.74	0.98	-1.10	1.01
se	0.14	0.02	0.10	0.02	0.13	0.02	0.10	0.03	0.11	0.03	0.12	0.03
t	-1.79	52.93	-5.56	52.93	-3.94	52.93	-5.36	29.75	-6.74	35.02	-8.80	38.26
variable 2	*kor3v*	*dif*	*kor3v*	*dif*	*kor3v*	*dif*	*kor3v*	*dif*	*kor2v*	*dif*	*kor1v*	*dif*
β	1.04	-0.29	1.52	-0.29	1.40	-0.29	1.48	-0.44	1.62	-0.47	1.83	-0.31
se	0.19	0.03	0.15	0.03	0.18	0.03	0.14	0.03	0.14	0.06	0.14	0.05
t	5.48	-10.72	-10.43	-10.72	7.93	-10.72	10.32	-7.05	11.35	-8.26	12.85	-5.76
Instruments	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*
	pp	*pp*	*eu*	*pp*	*mu*	*pp*	*bd*	*pp*	*bd*	*pp*	*bd*	*pp*
	b	*d*	*pp*	*d*	*pp*	*d*	*i1*	*d*	*i1*	*d*	*i1*	*d*
	d		*d*		*b*		*pp*		*pp*		*pp*	
	l		*l*		*l*		*d*		*d*		*d*	
							b		*b*		*b*	
							l		*l*		*l*	
Adjusted R^2	0.33	0.38	0.33	0.38	0.33	0.38	0.33	0.38	0.39	0.47	0.45	0.27
Breusch-Pagan test	0.00		0.00		0.00		0.00		0.00		0.00	

[4] All the results have not been reported for brevity, but are available upon request.

Three Stages Least Squares												
equation	(24)	(25)	(24)	(25)	(24)	(25)	(24)	(25)	(24)	(25)	(24)	(25)
variable 1	α_1	α_2	α_1	α_2	α_1	α_2	α_1	α_2	α_1	α_2	α_1	α_2
α	-0.38	0.86	-0.92	0.85	-0.77	0.87	-0.86	0.85	-1.09	0.95	-1.64	1.01
se	0.13	0.02	0.10	0.10	0.11	0.01	0.09	0.02	0.10	0.03	0.11	0.02
t	-3.03	55.44	-9.68	57.05	-6.74	57.80	-9.07	56.47	-10.40	35.81	-14.36	41.17
variable 2	*kor3v*	*dif*	*kor3v*	*dif*	*kor3v*	*dif*	*kor3v*	*dif*	*kor2v*	*dif*	*kor1v*	*dif*
β	1.26	-0.34	2.00	-0.32	1.80	-0.35	1.91	-0.31	2.08	-0.42	2.45	-0.30
se	0.18	0.03	0.13	0.02	0.16	0.02	0.13	0.03	0.14	0.05	0.13	0.05
t	6.84	-12.85	15.14	-12.86	11.13	-14.19	14.55	-12.52	15.32	-7.77	18.85	-6.10
Instruments	*x*	*x*	*eu*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*	*x*
	pp	*pp*	*x*	*pp*	*mu*	*pp*	*bd*	*pp*	*bd*	*pp*	*bd*	*pp*
	d	*d*	*pp*	*d*	*pp*	*d*	*i1*	*d*	*i1*	*d*	*i1*	*d*
	b		*d*		*b*		*pp*		*pp*		*pp*	
	l		*b*		*l*		*d*		*d*		*d*	
			l				*b*		*b*		*b*	
							l		*l*		*l*	
Adjusted R^2	0.38	0.38	0.33	0.38	0.33	0.38	0.33	0.38	0.39	0.47	0.45	0.27
Breusch-Pagan test	0.00		0.00		0.00		0.00		0.00		0.00	

Source: Author´s calculations

5. Conclusions

Extreme bounds analysis, in its most strict form would classify measures of structural similarities as not robust. This might explain why Baxter and Kouparitas as well as Böwer and Guillemineau report point estimates for structural similarities as not robust in their work. Using the Sala-i-Martin methodology, has proven that correlation coefficients of structural shares are robust determinants of business cycle synchronization. The results are not only robust across different levels of disaggregation, but also for value added and employment shares. The results are not robust across measures. Linear measures have proven to be bad proxies for structural similarities as determinants of business cycle synchronization. Convergence and business cycle synchronization with the USA also seem to play an important role. The degree of convergence is a robust determinant of business cycle synchronization with a negative point estimate. The lowest values of the t-statistics of GDP per capita distance are associated with the inclusion of measures of structural similarities. This might be explained by Imbs and Wacziarg's U-Shape specialization curve. When catching up countries are converging with developed, structural convergence increases and with it business cycle synchronization. This notion is confirmed by the results of a simultaneous equations estimation. On the other hand, the significance of business cycle synchronization with the USA is the lowest among the models including structural similarities. One explanation for this phenomenon might be that more similar economic structures foster a more similar response to external exogenous economic shocks.

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Appendix. Sectoral Division of Economies

Table A1. Sectoral Division of Economies

Sector	Description
Primary	A, B
Secondary	C, D, E, F
Tetriary	G, H, I, J, K, L, M, N, O, P, Q
A	agriculture, hunting and forestry
B	fishing
C	mining and quarrying
D	total manufacturing
E	electricity, gas and water supply
F	construction
G	wholesale and retail trade
H	hotels and restaurants
I	transport and storage and communication
J	financial intermediation
K	real estate, renting and business activities
L	public admin and defense; compulsory social security
M	education
N	health and social work
O	other community, social and personal services
P	private households with employed persons
Q	extra-territorial organizations and bodies
1	agriculture
2	forestry
10	mining of coal and lignite; extraction of peat
11	extraction of crude petroleum and natural gas and services
12	mining of uranium and thorium ores
13	mining of metal ores
14	other mining and quarrying
15	food and beverages
16	tobacco
17	textiles
18	wearing apparel, dressing and dying of fur
19	leather, leather and footwear
20	wood and of wood and cork
21	pulp, paper and paper
22	printing, publishing and reproduction
23	coke, refined petroleum and nuclear fuel

24	chemicals and chemical products
25	rubber and plastics
26	other non-metallic mineral
27	basic metals
28	fabricated metal
29	machinery, nec*
30	office, accounting and computing machinery
31	electrical machinery and apparatus, nec
32	radio, television and communication equipment
33	medical, precision and optical instruments
34	motor vehicles, trailers and semi-trailers
35	other transport equipment
36	manufacturing nec
37	recycling
40	electricity and gas
41	water supply
50	sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel
51	wholesale trade and commission trade, except of motor vehicles and motorcycles
52	retail trade, except of motor vehicles and motorcycles; repair of household goods
60	inland transport
61	water transport
62	air transport
63	supporting and auxiliary transport activities; activities of travel agencies
64	post and telecommunications
65	financial intermediation, except insurance and pension funding
66	insurance and pension funding, except compulsory social security
67	activities related to financial intermediation
70	real estate activities
71	renting of machinery and equipment
72	computer and related activities
73	research and development
74	other business activities
90	sewage and refuse disposal, sanitation and similar activities
91	activities of membership organizations nec
92	recreational, cultural and sporting activities
93	other service activities

Note: nec* - nowhere else classified
Source: http://euklems.net/ (13.05.2013)