The two-speed Europe in business cycle synchronization*

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Abstract

This paper evaluates the consequences of the financial and sovereign debt crises on the evolution of the business cycle synchronization among all the Euro Area members. Combining dynamic factor models with Markov-switching methodologies, we find that the Euro Area countries have recovered the level of business cycle synchronization exhibited before the Great Recession. However, we detect significant differences across countries in the required time to recover those levels.

Key words: Business cycle synchronization, monetary union, financial crisis, sovereign debt crisis.

JEL classification: E32, F44, C55.

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1. Introduction

The European Union (EU) was considered a successful process of integration, which could contribute to the economic development and the creation of wealth among its members. However, after the financial and the sovereign debt crises, the initial Euro-enthusiasm was followed by doubts about the advantages of the union. The differences in the economic performance of the EU members after these crises led to a phenomenon known as the *Two-Speed Europe* with two groups of countries: *Core countries*, formed by states with similar fiscal restraint and solid economic growth, and a second group of *Peripheral countries,* with weaker economic performance and higher fiscal deficits and public debt.

The collapse of the financial system after 2008, the sluggish economic recovery, and the deflationary pressures forced the European Central Bank (ECB) to employ a set of unconventional monetary policies. The disparity in the economic performance of the members, which shared the common expansionary monetary policy, also raised new concerns about the benefits of the existence of a monetary union.

For these reasons, analyzing the characteristics of the European countries' business cycles has been a source of research in the literature. Among others, Camacho et al. (2006) and Borsi and Metiu (2015) used a single country-specific indicator of aggregate economic activity as the Industrial Production Index or the Gross Domestic Product (GDP) to evaluate the economic convergence and business cycle synchronization across the members. Similarly, Di Giorgio (2016) implemented Markov-switching (MS) models to estimate the changes in the business cycle phases of the Euro Area (EA) and some Central and Eastern European countries (CEECs) by using one series of GDP per each CEEC and a series for the aggregate GDP of the EA. Nevertheless, as the author acknowledges, a univariate analysis may fail to capture some recessionary phases and, under the event of imperfect cyclical synchronization among macroeconomic categories, several variables per country should be considered for the estimation of the business cycle.

With the aim of filling this gap, this paper examines the disparities in the evolution of the business cycle synchronization across the members of the EA by proposing the following two-step procedure. In the first step, we obtain EA and country specific measures of aggregate economic activity by constructing a large dataset of cross-country series from several macroeconomic categories, whose co-movements are captured by a Dynamic Factor Model (DFM). In the case of Europe, previous studies have relied in DFMs to describe macroeconomic interactions between CEECs and some EA members, see Breitung and Eickmeier (2005) and Jimenez et al. (2013). Recently, Ferroni and Klaus (2015) estimate a DFM to analyze the business cycles characteristics of the four largest EA countries. In our proposal, we use the DFM of Kose et al. (2003) and Crucini et al. (2011) because it allows us to distinguish between common sources of variation in the Union and nation-specific factors.

In the second step, the measures of aggregate economic activities obtained in the factor analysis are used in the Markov-switching framework developed by Leiva-Leon (2017) to draw inferences about the synchronization of business cycles across the EA members. In contrast to other standard approaches, which summarize the overall level of synchronization in a single number for the entire sample period, this multivariate Markov-switching approach allows us to compute a measure of pairwise synchronization at each time observation along the sample. Therefore, we can examine the evolution of the time-varying dynamic interactions across the business cycles of the EA members.[1]

Using a recent dataset, which encompasses the financial and the sovereign debt crises, we find that, overall, the degree of synchronization of the EA members remained stable until the financial crisis, which implied a dramatic reduction in the degree of synchronization due to the different effects of this shock on each country. Thereafter, all the countries showed a progressive recovery in the synchronization to pre-crisis levels.

Notably, we find significant discrepancies in the recovery paths. Some countries have been able to catch up their pre-crisis level of synchronization very fast, letting even some countries to

[1] Egert and Kocenda (2011) examine the time-varying synchronization across European stock markets.

improve their initial levels. However, some EA members are still far from recovering their pre-crisis degrees of business cycle synchronization.[2] These findings support the existence of a *Two-Speed Europe* in terms of synchronization.

The rest of the paper is organized as follows. Section 2 describes the model and the measure of synchronization between the common factor and each of the country-specific factors. Section 3 examines the empirical results. Section 4 states the conclusions.

2. A model to examine synchronization

This section describes the procedure applied for the estimation of the latent factors that summarize the common behavior of the economic indicators. In addition, the section also describes the process to measure the synchronization among them.

2.1. Dynamic factor model

The estimation of the factors is based on the DFM proposed in Crucini et al. (2011). This is a suitable framework to deal with the large dimension of the dataset and the specific characteristic of the cross-country data. In particular, each macroeconomic indicator in a given country is assumed to be explained by three components: a common latent factor affecting all the series in the dataset; a second latent factor, which only affects the group of series in a particular country; and an idiosyncratic term, which is specific to each series. Hence, every data observation is decomposed according to the following equation:

$$y_{i,t} = \alpha_i + \beta_{EA,i} f_{EA,t} + \beta_{n,i} f_{n,t} + \varepsilon_{i,t}, \tag{1}$$

where $f_{EA,t}$ is the EA factor; $f_{n,t}$ is the country factor; $n = 1, \ldots, N$, where N is the number of countries; and $\varepsilon_{i,t}$ is the idiosyncratic component. Observable series at period t are denoted as

[2] In an independent proposal, based on GDP data at the regional level of the NUTS2 classification, Gadea-Rivas et al. (2017) have also documented the different patterns in the synchronization in Europe since the introduction of the euro.

$y_{i,t}$ for $i = 1, \dots, MxN$, where M is the number of macroeconomic series per country. The factor loadings, $\beta_{EA,i}$ and $\beta_{n,i}$, measure the amount of variation in $y_{i,t}$ that is explained by each factor.

The dynamic of the factors is assumed to follow an autoregressive process of order p_k:

$$f_{k,t} = \emptyset_{f_k,1} f_{k,t-1} + \emptyset_{f_k,2} f_{k,t-2} + \dots + \emptyset_{f_k,p} f_{k,t-p_k} + u_{f_k,t}, \tag{2}$$

where $E[u_{f_k,t} u_{f_k,t}] = \sigma^2_{f_k}$, $k = 1, \dots, K$, and K is the number of latent factors.

In addition, the idiosyncratic terms, $\varepsilon_{i,t}$, are assumed to follow autoregressive processes of order q_i:

$$\varepsilon_{i,t} = \emptyset_{i,1} \varepsilon_{i,t-1} + \emptyset_{i,2} \varepsilon_{i,t-2} + \dots + \emptyset_{i,q_i} \varepsilon_{i,t-q_i} + u_{i,t}, \tag{3}$$

where $E[u_{i,t} u_{j,t-s}] = \sigma^2_i$ for $i = j, s = 0,$ and 0 otherwise; $E[u_{f_k,t} u_{i,t-s}] = 0$ for all $k, i,$ and s.[3] The error terms $u_{f_k,t}$ and $u_{i,t}$ are assumed to be normally distributed variables with zero mean. In the empirical application, the dataset is formed by eighteen countries ($N = 18$), and there are nineteen dynamic unobserved factors ($K = N + 1$) that represent the common interrelations that take place in the cross-country dataset.

The estimation of the multifactor model (1) - (3) for a large set of countries requires the estimation of the latent factors and a sizable number of parameters relating them with the observable series. Moreover, given the short life of the EA, the temporal dimension of the dataset is relatively small with respect to cross section dimension. For these reasons, we apply the Bayesian estimation procedure proposed by Kose et al. (2003) and Crucini et al. (2011), which has been shown to work efficiently in this context.[4]

Let θ be the set of parameters to be estimated, F the vector of dynamic latent factors ($KTx1$) with Gaussian probability density $p_f(F)$, and Y the vector of observable data ($MNTx1$). The

[3] Following Kose et al. (2003) and Crucini et al. (2011), we set the lag length of the autoregressive processes to three.
[4] Kose et al. (2003) estimate world, region and country factors for 60 countries with 30 years of annual data.

Gaussian probability density for the observable series conditional on the factors and the parameters is $p_y(Y \mid \theta, F)$. According to the Bayes' theorem, for a given prior distribution of θ, $p(\theta)$, the joint posterior distribution for the factors and parameters is the product of the likelihood and prior:

$$p(\theta, F \mid Y) = p_y(Y \mid \theta, F)\, p_f(F) p(\theta) \tag{4}$$

However, while the joint posterior is difficult to handle, a sample of θ and F can be generated by means of Markov Chain Monte Carlo methods sampling from the conditional density of the parameters given factors and data and the conditional density of the factors given parameters and data. Specifically, the parameters and the factors are generated by sampling both iteratively from the next two steps:

1. Sampling θ^1 from the conditional density $p(\theta \mid F^0, Y)$ where F^0 is a starting value in the support of the posterior distribution of F,

2. Sampling F^1 from the conditional density $p(F \mid \theta^1, Y)$. In a first step, we sample from the distribution of the EA factor conditional on the parameters and the specific country factors. In a second step, we sample from the distribution of each country factor conditional on the EA factor and the parameters.

These two steps generate in each stage of the Markov Chain drawings $\{\theta^j, F^j\}$ for $j = 1, \ldots, J$, where $\theta^j \sim p(\theta \mid F^{j-1}, \mathrm{Y})$ and $F^j \sim p(F \mid \theta^{j-1}, \mathrm{Y})$. Given the proper priors, this iterative process produces a realization of a Markov chain whose invariant distribution is the joint posterior of the model parameters and the unobservable factors (Otrok and Whiteman 1998).
The posterior distribution for the parameters is built by computing the likelihood for the first p_i observations, sequentially conditioning to compute the rest of the likelihood and using the usual prior densities which are considered sufficiently uninformative. To be precise, the prior for the factor loadings is $(\beta_{EA,i}\, \beta_{n,i})' \sim N(0, (0.001 * I_2)^{-1})$, where I_2 is the $2x2$ identity matrix.

Autoregressive parameters for both, the idiosyncratic components and the factors, $\emptyset_i = (\emptyset_{i,1}, \emptyset_{i,2}, \emptyset_{i,3})'$ and $\emptyset_{f_k} = (\emptyset_{f_k,1}, \emptyset_{f_k,2}, \emptyset_{f_k,3})'$, follow a prior distribution $N(0, \Sigma)$ with

$$\Sigma = \begin{bmatrix} 0.85 & 0 & 0 \\ 0 & 0.5 & 0 \\ 0 & 0 & 0.25 \end{bmatrix}. \tag{5}$$

This represents the belief that data in growth rates is not serially correlated and that the impacts of the lags mitigate as the lag length increases. As in the previous literature, to identify the scale of the latent factors, $\sigma_{f_k}^2$ are set equal to a constant. In addition, the prior distribution for σ_i^2 is $IG(6, 0.001)$.

Finally, the conditional distribution of the factors given the data and the parameters is derived as in Otrok and Whiteman (1998). In particular, we compute the joint density for the observable data and the latent factors given the parameters as the product of NMK independent Gaussian densities. Then, we use this joint distribution to obtain the conditional distribution of the factors given the data and the parameters.

2.2. Synchronization

This section describes the procedure followed to evaluate the potential variations in the cyclical interdependencies between the EA factor and each of the country-specific factors. Using the bivariate Markov-switching model proposed by Leiva-Leon (2017), we obtain a full characterization of the regime inferences and inferences on the type of synchronicity that the Euro Area factor and the specific-country factors bear at each period of time.

Following the previous notation, let $f_{k,t}$ be the unobservable dynamic factors that describe the macroeconomic co-movements among the countries included in the panel of cross-country data. When index $k = EA$, the factor describes the evolution of the EA aggregate economic activity, while it represents the country-specific economic activity when $k = n$, where $n = 1, \ldots, 18$. Therefore, $f_{k,t}$ can be modeled using a MS model as proposed by Hamilton (1989), where the dynamics of the factors depends on an unobserved state variable ($S_{k,t}$) that controls the regime changes, an idiosyncratic component, $\epsilon_{k,t}$, and a set of model parameters, Θ_k, where $k = EA, n$. Each of the state variables, $S_{EA,t}$ and $S_{n,t}$ evolve according to an irreducible two-state Markov chain, whose transition probabilities are given by:

$$Pr\big(S_{k,t} = j \mid S_{k,t-1} = i \big) = p_{k,ij}, \tag{6}$$

To compute inference on the interactions between the two state variables, we adopt the following bivariate two-state Markov-switching specification:

$$\begin{bmatrix} f_{EA,t} \\ f_{n,t} \end{bmatrix} = \begin{bmatrix} \mu_{EA,0} + \mu_{EA,1} S_{EA,t} \\ \mu_{n,0} + \mu_{n,1} S_{n,t} \end{bmatrix} + \begin{bmatrix} \epsilon_{EA,t} \\ \epsilon_{n,t} \end{bmatrix}, \tag{7}$$

$$\begin{bmatrix} \epsilon_{EA,t} \\ \epsilon_{n,t} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_{EA}^2 & \sigma_{EA,n} \\ \sigma_{EA,n} & \sigma_n^2 \end{bmatrix} \right). \tag{8}$$

for $i, j = 0, 1$ and $k = EA, n$. If the state variable $S_{k,t} = 0$, $f_{k,t}$ is in regime 0 with mean equals to $\mu_{k,0}$, while if $S_{k,t} = 1$, $f_{k,t}$ is in regime 1 with mean equals to $\mu_{k,0} + \mu_{k,1}$. If we assume $\mu_{k,1} > 0$, the latent variable $S_{k,t}$ identifies periods of *low* and *high* economic performance, which are interpreted as recessions and expansions, respectively.

Phillips (1991) was pioneering in evaluating the transmission of business cycles between regions in the context of bivariate Markov-switching processes. Although there are two possible states for each separate region, modeling the interactions would require a new unobservable state variable $S_{EA,n,t}$ that encompasses the four different combinations: $S_{EA,n,t} = 1$ when $\big(S_{EA,t} = 0, S_{n,t} = 0\big)$, $S_{EA,n,t} = 2$ when $\big(S_{EA,t} = 1, S_{n,t} = 0\big)$, $S_{EA,n,t} = 3$ when $\big(S_{EA,t} = 0, S_{n,t} = 1\big)$, and $S_{EA,n,t} = 4$ when $\big(S_{EA,t} = 1, S_{n,t} = 1\big)$.

Regarding the case of business cycle interdependence between the business cycles of two regions, Phillips (1991) describes two extreme cases. The first case characterizes pairs of regions for which their individual business cycle fluctuations are completely independent. In this case, the separate regime-shifting processes, $S_{EA,t}$ and $S_{n,t}$, are independent and

$$\Pr\left(S_{EA,t} = j_{EA}, S_{n,t} = j_n\right) = \Pr\left(S_{EA,t} = j_{EA}\right) \Pr\left(S_{n,t} = j_n\right), \tag{9}$$

where $j_{EA} = 0,1$ and $j_n = 0,1$. In the opposite case of perfect synchronization (or dependence), both regions share the state of the business cycle and the probabilities of $S_{EA,n,t}$ are in fact those of one of the regions, implying that $S_{EA,t} = S_{n,t} = S_t$, and that

$$\Pr\left(S_{EA,t} = j_{EA}, S_{n,t} = j_n\right) = \Pr\left(S_t = j\right), \tag{10}$$

where $j = 0,1$. Bengoechea, Camacho and Perez-Quiros (2006) proposed a new framework to measure the degree of business cycle correlation between EA and country *n*. These authors realized that independence and perfect synchronization are two extreme possibilities that never occur in practice. For two regions, the actual probabilities will be a linear combination of these two extremes:

$$\Pr\left(S_{EA,t} = j_{EA}, S_{n,t} = j_n\right) = \delta \Pr(S_t = j) + (1 - \delta) Pr\left(S_{EA,t} = j_{EA}\right) \Pr\left(S_{n,t} = j_n\right). \tag{11}$$

Then, δ, which is estimated from the data, measures the degree of overall pairwise business cycle synchronization.

Leiva-Leon (2017) went one step further, although at the cost of complicating the approach a bit. The contribution of this author was summarizing the information about the relationship of dependency between the two separate latent variables, by defining another latent variable $V_{EA,n,t}$ that governs the transition between the two extreme cases, independent cycles and perfect synchronization. This latent variable $V_{EA,n,t}$ is equal to 1 if the business cycle phases are in a fully synchronized regime at time *t*, and 0 otherwise.

To complete the statistical characterization of the model, $V_{EA,n,t}$ is also assumed to evolve according to a two-state Markov chain with transition probabilities given by

$$\Pr\left(V_{EA,n,t} = j_v \mid V_{EA,n,t-1} = i_v \right) = p_{v,ij} \text{ for } i_v, j_v = 0, 1. \tag{12}$$

The potential regimes of the model implies that the four cases of the regime-switching variable $S_{EA,n,t}$ could appear either when $V_{EA,n,t} = 1$ or when $V_{EA,n,t} = 0$. The resulting eight different states are summarized by the latent variable $S^*_{EA,nt}$ for each period of time t. In particular, the eight different regimes are

$$S^*_{EA,n,t} = \begin{Bmatrix} 1, & if\ S_{EA,t} = 0, & S_{n,t} = 0, & V_{EA,n,t} = 0 \\ 2, & if\ S_{EA,t} = 0, & S_{n,t} = 1, & V_{EA,n,t} = 0 \\ 3, & if\ S_{EA,t} = 1, & S_{n,t} = 0, & V_{EA,n,t} = 0 \\ 4, & if\ S_{EA,t} = 1, & S_{n,t} = 1, & V_{EA,n,t} = 0 \\ 5, & if\ S_{EA,t} = 0, & S_{n,t} = 0, & V_{EA,n,t} = 1 \\ 6, & if\ S_{EA,t} = 0, & S_{n,t} = 1, & V_{EA,n,t} = 1 \\ 7, & if\ S_{EA,t} = 1, & S_{n,t} = 0, & V_{EA,n,t} = 1 \\ 8, & if\ S_{EA,t} = 1, & S_{n,t} = 1, & V_{EA,n,t} = 1 \end{Bmatrix}. \tag{13}$$

Finally, the joint dynamic of $S_{EA,t}$ and $S_{n,t}$ is described by a weighted average between the fully synchronized and fully independent scenarios as follows:

$$\begin{aligned} \Pr\left(S_{EA,t} = j_{EA}, S_{n,t} = j_n\right) &= \Pr\left(V_{EA,n,t} = 1\right)\Pr\left(S_t = j\right) \\ &\quad + \left(1 - \Pr(V_{EA,n,t} = 1)\right)\Pr\left(S_{EA,t} = j_{EA}\right)\Pr\left(S_{n,t} = j_n\right), \end{aligned} \tag{14}$$

where $\Pr\left(V_{EA,n,t} = 1\right) = \delta_t$ measures the dynamic synchronicity between $S_{EA,t}$ and $S_{n,t}$ and determines the weights attributed to each scenario.[5] Therefore, in our empirical application, δ_t quantifies the time-varying degree of synchronization between the business cycle of the EA and the particular macroeconomic fluctuations in each country included in the dataset along the sample period.

3. Empirical results

[5] Leiva-León (2017) describes a Bayesian method to estimate the model parameters and to compute inferences on the state variables.

This section describes the selected data, the results regarding the estimation of the factors as a summary of the aggregate economic activity, and the characterization of the evolution of the business cycle synchronization among the EA members.

3.1. The data

The dataset is composed by several macroeconomic indicators for all the EA members. As suggested by Kose et al. (2003) and Crucini et al. (2011), we select macroeconomic series of production, consumption and investment for each country. In particular, we use the demeaned growth rates of GDP, Household & NPISH Final Consumption Expenditure, and Gross Fixed Capital Formation. The seasonally adjusted series were downloaded from the Eurostat database at a quarterly frequency.

Data availability differs for each of the EA members. Thus, to consider a balanced dataset, our effective sample spans the period between the first quarter of 2000 to the last quarter of 2015 for all the nineteen countries of the EA but Cyprus.[6] Hence, our dataset is composed by three economic indicators from 18 different countries and 64 quarterly observations, which cover the last 16 years since the introduction of the euro as a single currency in 1999.

3.2. Aggregate economic activity

Macroeconomic co-movements along the eighteen countries in the dataset are estimated through a common EA factor and the particular co-movements within each country through the country-specific factors. Figure 1 presents the results of the estimation of the latent factors. For the sake of space, and due to the large amount of countries composing the EA, the figure only depicts some illustrative examples. In particular, the figure represents the factors for the EA, Spain and Italy, along with 33 and 66-percent quantile bands (doted lines); these tight bands show that the factors are accurately estimated. The upper graph describes the evolution of the EA factor together with the periods defined by the Euro Area Business Cycle Dating Committee of the Center for Economic Policy Research (CEPR) as recessions (shaded areas).

[6] The database from Eurostat has only a few observations available for this country.

Insert Figure 1 about here

The figure shows that the EA factor is able to track the economic evolution of the EA according to the dating of the CEPR. Overall, the factor takes negative values during the two recession periods between 2008.Q1-2009.Q2 and 2011.Q3-2013.Q1 and positive values elsewhere. The estimates of the EA factor suggest that the downturn at the beginning of 2008 was much severe than the recession that followed the European sovereign debt crisis of 2011 and measures the economic recovery between the two recessions.

However, the factor in Spain (middle graph) shows how the Spanish economy kept a low economic performance between the two recessions and starts an expansion after the second quarter of 2013. On the other hand, the factor in Italy (lower graph) shows that this country was more affected by the sovereign debt crisis during the second recession. These results provide an illustrative example of the different reactions of the EA members to the economic events that affected Europe after 2008.

Regarding others country-specific factors not included in Figure 1, some countries recover earlier than the Spanish economy from the first recession and show a stable improvement during the following years, not being affected by the second recession severely.[7] This is the case of Belgium, Estonia, France, Germany, Latvia, Lithuania, Slovenia and Slovakia factors. In the case of Greece, the estimated factor shows that the Greek economy had a lower economic performance between the two recessions as in the case of Spain. Finland and Portugal show a pattern similar to Italy, being more affected by the second crisis. Finally, the factors corresponding to Luxembourg, Ireland, Malta, Austria and the Netherlands remained relatively stable during that period.

3.3. Business cycle synchronization

[7] These results are omitted to save space. However, they are available from the authors upon request.

Once the latent factors are estimated, they are included in the Markov-switching specification described in Section 2. Figure 2 depicts the comparison of the regime switches of the EA factor with those corresponding to the Spain factor. The upper and middle graphs represent the MS filtered probabilities of regime switches in the EA and Spain factors respectively. These estimated probabilities take values close to one during the CEPR recession periods. Hence, they are interpreted as an accurate characterization of the business cycle phases estimated with the information included in a large panel of cross-country data. The filtered probabilities for the EA factor show a decrease between the two recession periods. However, given that the Spanish economy showed a worse economic performance at that dates (see Figure 1), its recession probabilities are higher during that period and remain closer to one.

The lower graph depicts the probability of synchronization in the business cycle phase changes of the EA and Spain factors. This probability shows high values and a slight positive trend during the first part of the sample since the introduction of the euro. In the period between the two recessions, synchronization decreases drastically due to the poorer economic performance of Spain with respect to the EA. Then, the degree of synchronization rises again as the EA economy enters into the second recession. After that, synchronization shows a slight decrease since the middle of the second recession given that Spain needed more time to begin the economic recovery. Finally, synchronization increases again once Spain starts to recover in the second quarter of 2013 and reaches values like those observed at the beginning of the sample.

Insert Figure 2 about here

Figure 3 shows the estimated pairwise synchronization of the EA economic activity and Germany, Italy, France and Portugal. Germany shows a high level of synchronization along the sample period. According to this figure, the German business cycles become less synchronized after the financial shock and during the second CEPR recession. However, those drops take place with a delay with respect to the beginning of the CEPR recessions. These facts highlight the robust connection of the German economy to the EA fluctuations, especially during the first stages of the financial and the debt crisis.

Italy, France and Portugal present a lower level of synchronization during the pre-recessions period at the beginning of the sample. In these three countries, synchronization drops after the financial crisis and shows a significant increase after 2009. In the case of France and Portugal, the high synchronization is only slightly reduced during the second recession between 2011 and 2013. Notably, the level of synchronization of these countries shows an improvement at the end of the sample with respect to the period between the introduction of the euro and the first recession.

Insert Figure 3 about here

Figure 4 describes the evolution of the synchronization of EA and Greece, Austria, Finland, Slovakia, and Slovenia. As in Figure 3, there is a fall in synchronization that took place close to the financial crisis. The lack of synchronization in Greece, Finland and Austria started earlier while macroeconomic fluctuations in Slovakia and Slovenia decoupled once the recession had started. However, the effects of the recessions were more persistent in the second set of countries. Synchronization remains at low values for a longer time after 2008 and does not improve before the second recession (Finland and Slovenia) or falls again after 2011 (Greece, Austria and Slovakia). Furthermore, these countries show higher levels of synchronization before the recessions than at the end of the sample, suggesting that they will require more time to reconnect their macroeconomic behavior with the EA fluctuations.

Insert Figure 4 about here

The results for Ireland, the Netherlands, Latvia and Luxemburg are presented in Figure 5. In contrast to the analysis of the EA members showed by Figures 3 and 4, this set of countries shows a progressive decrease of synchronization and reaches the maximum level of desynchronization during the 2011-2013 recession. This decline starts earlier in the case of Ireland and the Netherlands while it is more abrupt in Latvia and Luxembourg. Although Ireland, the Netherlands and Latvia show an increasing trend in their estimates at the end of the sample, only Luxemburg reaches a degree of synchronization as high as the one observed before the recessions.

Insert Figure 5 about here

Finally, Figure 6 incorporates the results corresponding to Belgium, Estonia, Malta and Lithuania. In the case of Malta, the figure depicts an increasing trend in its synchronization since the beginning of the sample until the start of the first recession. After that date, it decreases constantly and reaches a minimum in 2013. Once the second recession ended, synchronization improves until the end of the sample. As in the analysis of the countries included in Figure 3, Belgium, Estonia and Lithuania suffer from a drastic decrease in their synchronization during the first recession, while it recovers quickly after this period. In particular, Belgium and Estonia react very fast in terms of synchronization after the financial crisis and required a short period to recover from that shock. Instead, Lithuania desynchronizes some quarters later after the start of the first recession although, thereafter, its synchronization rises sharply before the second recession. Nevertheless, the main difference between these countries and those depicted in Figure 3 is that none of them shows an increase in its degree of synchronization after the recessions with respect to the beginning of the sample.

Insert Figure 6 about here

4. Conclusions

The global effects of the financial crisis and its resulting consequences on government debt levels forced central bankers to implement unconventional monetary stimuli to avoid an economic collapse. In the case of EA, this was particularly challenging because a single and highly expansionary monetary policy was applied to a large set of countries in different phases of their respective business cycles.

This paper evaluates the consequences of these historic events on the evolution of the business cycle synchronization among all the members of the EA using a large panel of cross-country data. The analysis focuses on combining the dimension reduction properties of DFMs with a MS specification that provides a time-varying measure of synchronization for each observation along the sample. Our results show that, although the countries exhibit an overall decline in the synchronization in the financial crisis, they recover the levels of synchronization that characterized the pre-recessions period.

However, we also find that there are notable differences in the magnitude of the fall in synchronization and in the period of time required to recover the pre-recessions synchronization levels. Hence, the findings provided here support the presence of a *Two-Speed Europe* after the financial crisis in terms of economic synchronization. Countries as Germany, France, Italy, Spain, Portugal, Belgium, Estonia and Lithuania recover quickly their level of synchronization after the first recession and some of them even improve it with respect to the period before 2008. On the contrary, Ireland, the Netherlands, Luxemburg, Latvia and Malta suffered a larger desynchronization after 2011 and show a slower recovery. Greece, Austria, Slovakia, Slovenia and Finland keep a decrease on their levels of synchronization during a larger period between the two recessions.

Therefore, we fail to find evidence suggesting that the recent implementation of the unconventional monetary stimuli applied by the ECB amplified the desynchronization of the EA members. By contrast, these countries show an increasing degree of synchronization after 2013, some of which reached an improvement with respect to their pre-recession synchronization levels.

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Figures

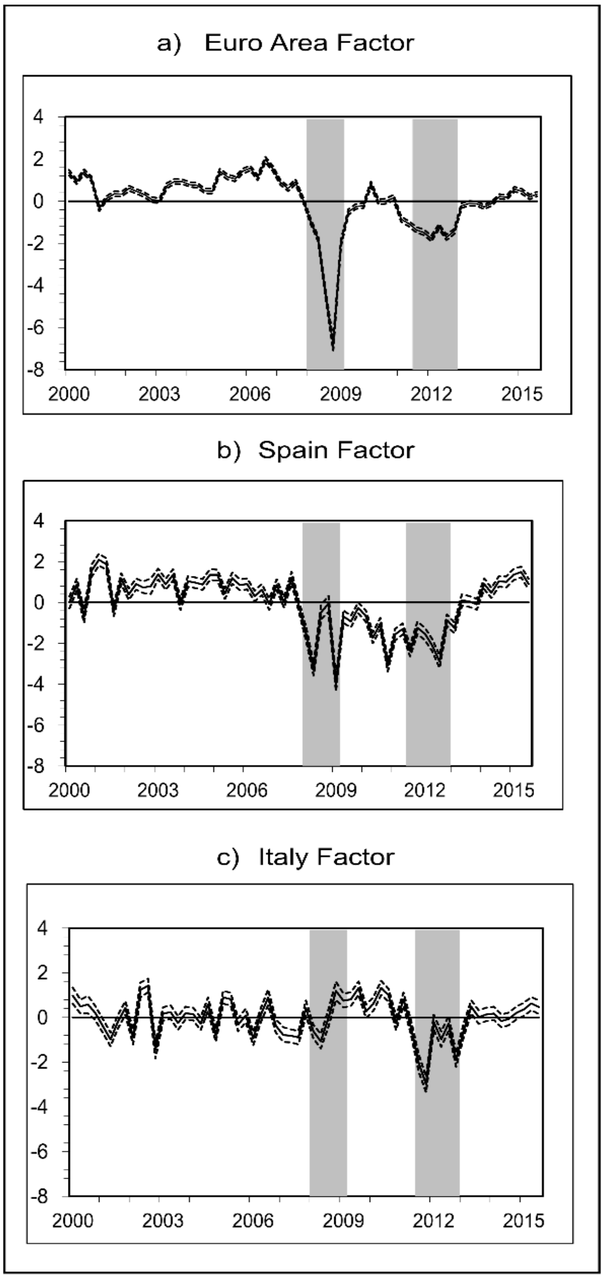

Fig 1 The estimated Euro Area (a), Spain (b) and Italy (c) factors

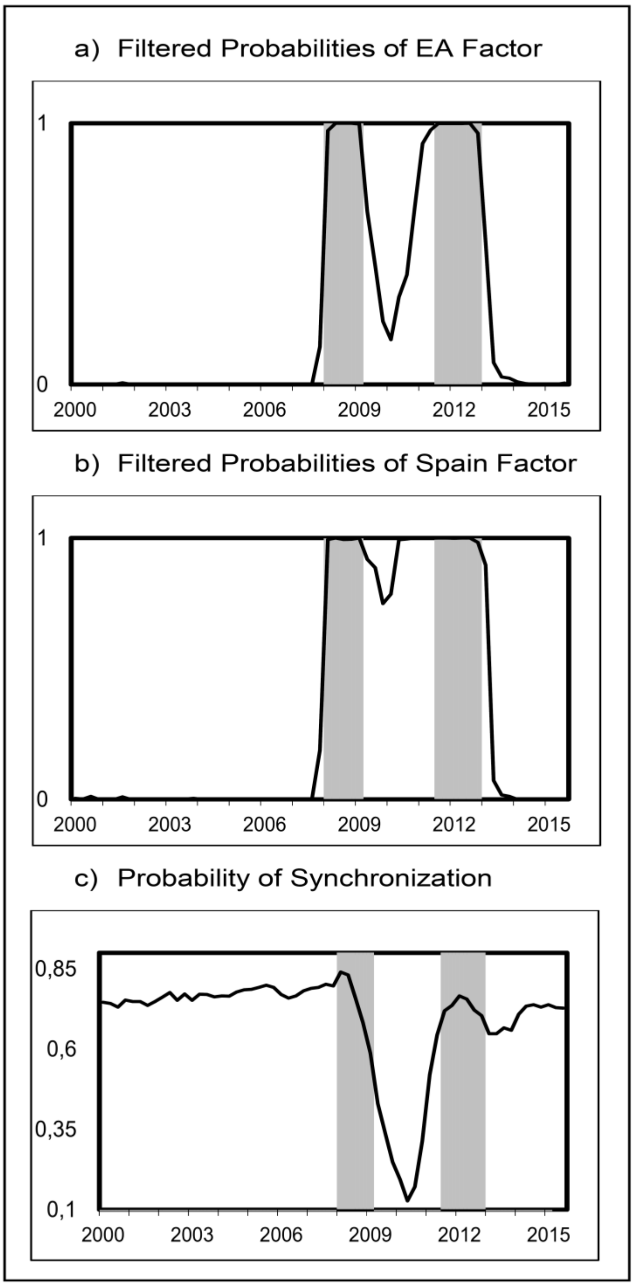

Fig 2 Filtered probabilities of regime switches for the EA factor (a) and the Spain factor (b). Probability of synchronization between the regime changes of EA and Spain factors (c)

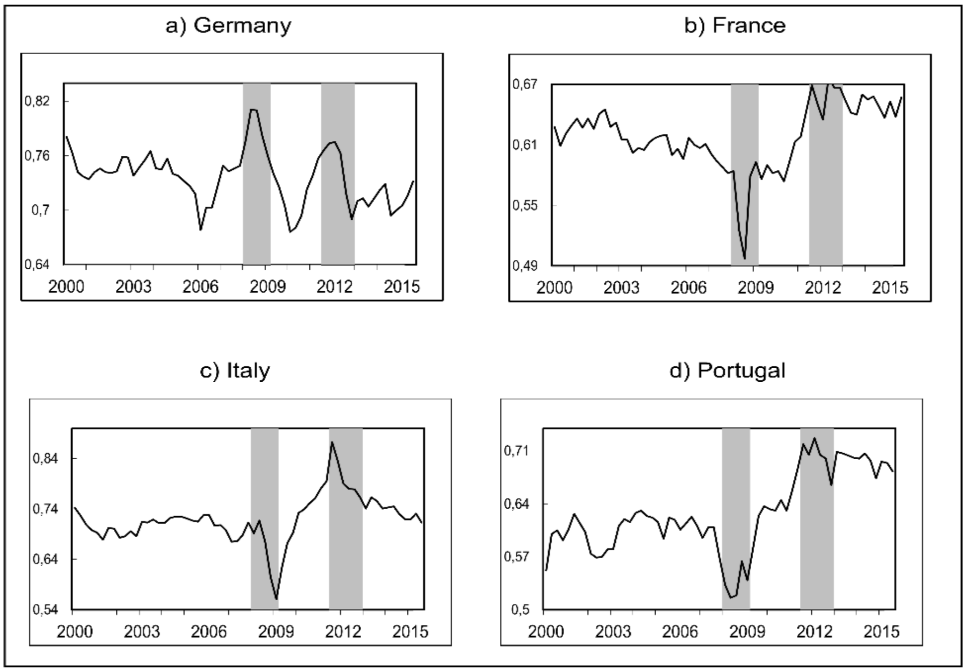

Fig 3 Probabilities of synchronization between the regime switches of the Euro Area and the Germany (a), the France (b), the Italy (c), and the Portugal (d) factors

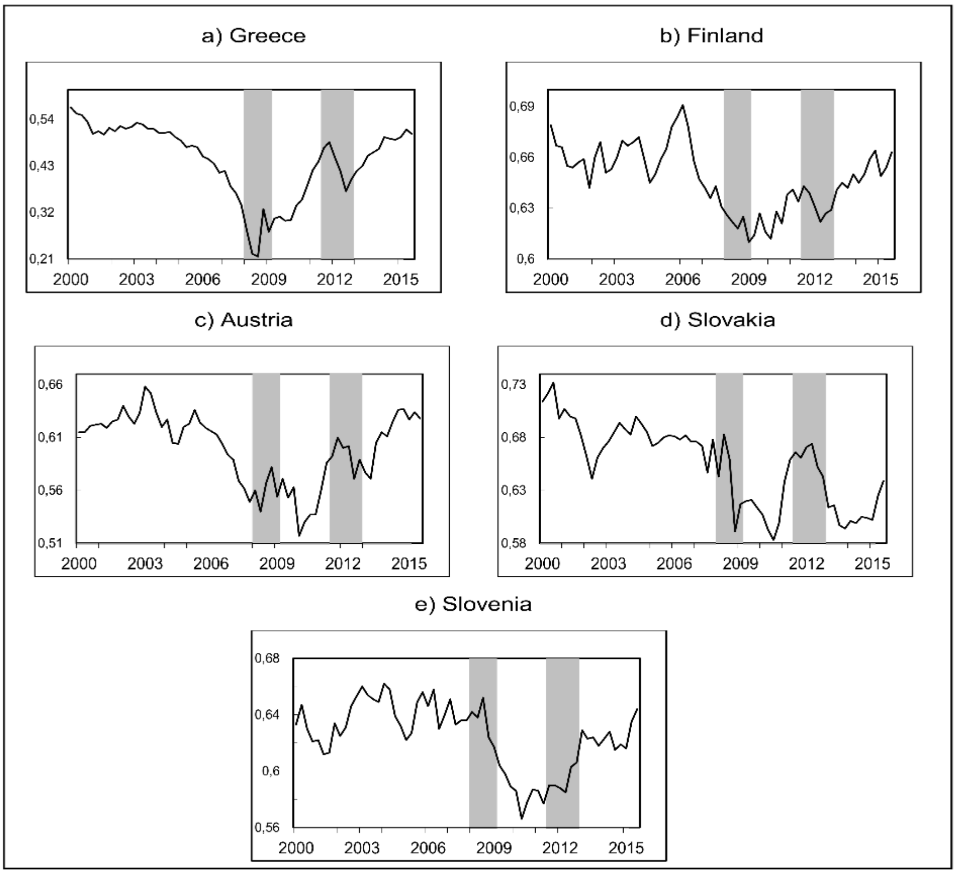

Fig 4 Probabilities of synchronization between the regime switches of the Euro Area and the Greece (a), the Finland (b), the Austria (c), the Slovakia (d), and the Slovenia (e) factors

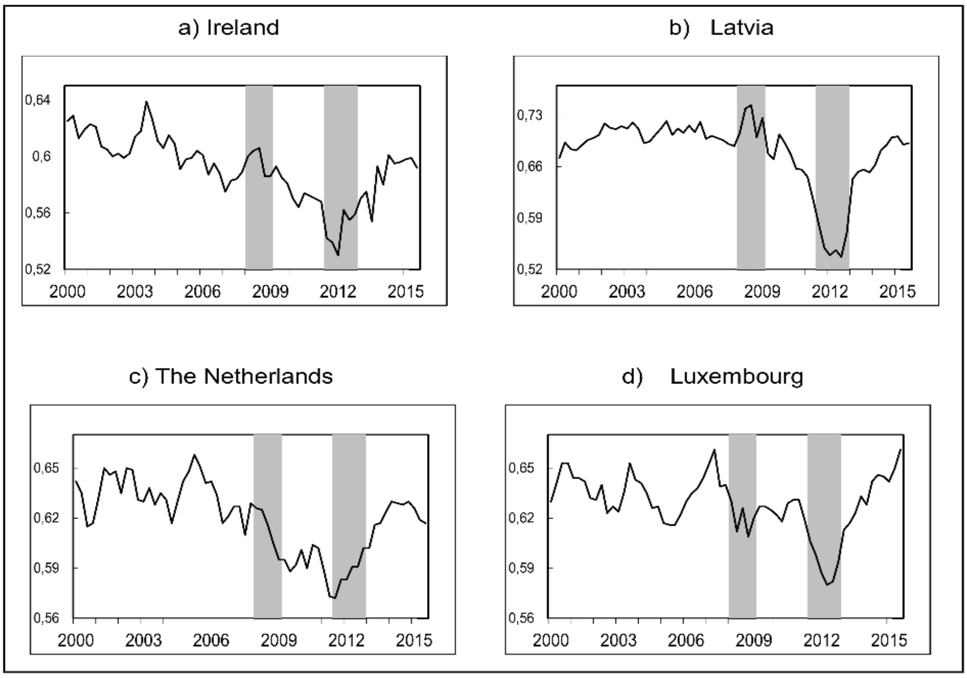

Fig 5 Probabilities of synchronization between the regime switches of the Euro Area and the Ireland (a), the Latvia (b), the Netherlands (c), and the Luxembourg (d) factors

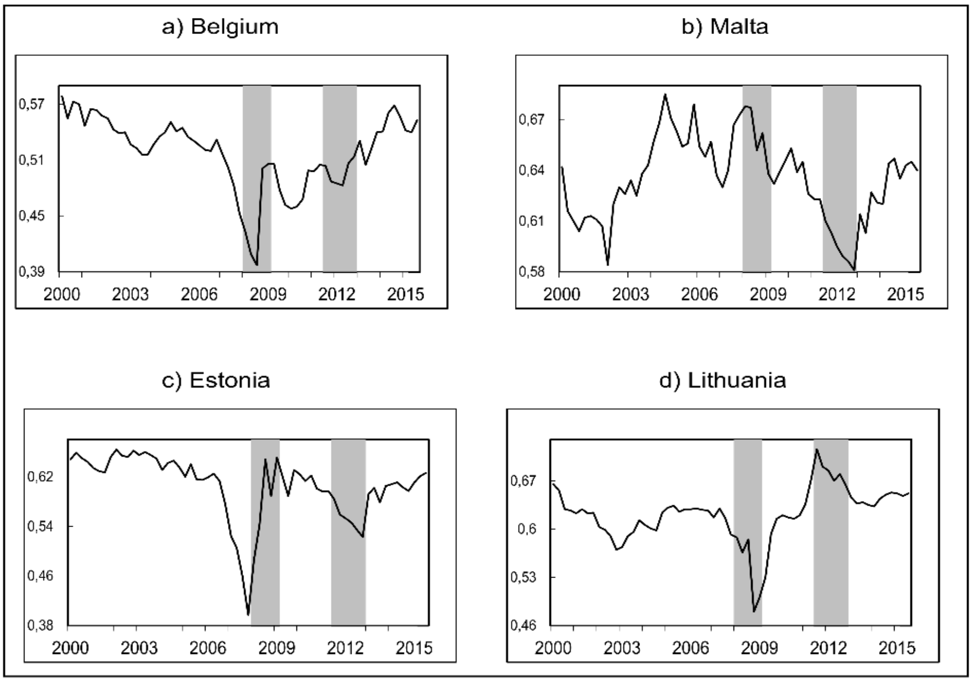

Fig 6 Probabilities of synchronization between the regime switches of the Euro Area and the Belgium (a), the Malta (b), the Estonia (c), and the Lithuania (d) factors