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Empirical Essays on Business Cycles

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Mira a las estrellas, pero no te olvides de encender la lumbre del hogar. Proverbio alemán

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I conclude with this beautiful poem of J. W. von Goethe that I find very inspiring.

Hat alles seine Zeit.	Todo tiene su tiempo.
Das Nahe wird weit.	Lo cercano se tornará lejano.
Das Warme wird kalt.	Lo cálido se volverá frio.
Der Junge wird alt.	El joven se hará viejo.
Das Kalte wird warm.	Lo frío se volverá cálido.
Der Reiche wird arm.	El rico se convertirá en pobre.
Der Narre gescheit.	El necio se volverá sensato.
Alles zu seiner Zeit.	Todo a su tiempo.

Alcalá de Henares (Madrid), May 2012

Abstract

This dissertation consist of four empirical essays. In the first essay, I study the synchronization of the business cycles across European countries and several industrialized countries with the aim of estimating how costly the economic integration is. I provide a comprehensive methodology to characterize the comovements across the economies. And I find that the creation of the European Monetary Union (EMU) has not significantly increased the cyclical comovement and show evidence against the existence of one common European cycle. This result puts a question mark on those works that either implicitly or explicitly assume that it exists.

In the second essay, I further investigate the existence of one common European cycle focusing on the characteristics of the business cycles: duration, amplitude and concavity or convexity of the recessions and the expansions. Moreover, I present a robust methodology based on stationary bootstrap for dating and characterizing the business cycles. I find that the characteristics are very different across countries, that these differences have not decreased over time, and I identify four groups of countries.

In the third essay, I conduct an empirical study of the possible factors that explain the business cycles comovements across countries. The main finding is that trade is fundamental, in agreement with most of the literature. However, in contrast to other works in the literature, the structural differences in the productive specialization, the fiscal policy, the savings ratio or the labor productivity have a significant role in explaining the cyclical divergences.

And finally, in the fourth essay I identify several stylized facts in relation to the correlations and variances of several macroeconomic variables. I show that they are time-varying and tend to be higher in recessions than in expansions. I propose a parsimonious extension of the standard Dynamic Factor Model to take these facts into account. In addition, my proposal improves the forecasting performance in the short-run, especially in moments of high uncertainty. Furthermore, it delivers an estimate of the common factor's volatility that can be interpreted as a measure of broad macroeconomic risk.

Resumen

Esta tesis consiste en cuatro ensayos empíricos. En el primer ensayo, estudio la sincronía cíclica entre los países Europeos y algunas economias desarrolladas con el objetivo de estimar el coste del proceso de integración económica. Además aporto una metodología bastante completa para caracterizar los comovimientos. Y encuentro que la creación de la Unión Monetaria Europea (UME) no ha incrementado de forma significativa los comovimientos cíclicos y muestro evidencia en contra de la existencia de un ciclo común europeo. Este resultado pone un interrogante a aquellos trabajos que de forma implícita o explícita asumen su existencia.

En el segundo ensayo, continuo investigando sobre la existencia de un ciclo común europeo concentrándome en las características del ciclo: duración, amplitud y concavidad o convexidad de las recesiones y expansiones. Además, propongo un método robusto basado en bootstrap estacionario para el fechado y caracterización de los ciclos económicos. Encuentro que las características son muy distintas por países, que estas diferencias no se han reducido con el tiempo, e identifico cuatro grupos de países.

En el tercer ensayo, desarrollo un estudio empírico sobre los posibles factores que explican los comovimientos cíclicos entre países. El principal resultado es que el comercio es fundamental, lo que está de acuerdo con la mayor parte de la literatura. Sin embargo, y en contraste con otros trabajos de la literatura, diferencias estructurales en la especialización productiva, la política fiscal, la tasa de ahorro o la productividad del trabajo también tienen un papel significativo en explicar estas divergencias cíclicas.

Y por último, en el cuarto ensayo identifico varios hechos estilizados en relación a las varianzas y las correlaciones de varias variables macroeconómicas. Muestro que éstas cambian con el tiempo y que tienden a ser mayores durante las recesiones que en las expansiones. Propongo una extensión parsimoniosa del modelo estándar factorial dinámico que recoge estos hechos. Además, mi propuesta mejora la predicción a corto plazo, especialmente en momentos de elevada incertidumbre. Por otra parte permite obtener una estimación de la volatilidad del factor común, que puede ser interpretada como una medida de riesgo macroeconómico en sentido amplio.

Memoria

Antecedentes

Hace más de 50 años seis países Europeos - Bélgica, Francia, Italia, Alemania, Luxemburgo y Holanda - decidieron crear la Comunidad Económica Europea (CEE). Ha sido un largo camino desde entonces en el que se han hecho grandes progresos en la integración económica. De hecho, la Unión Europea (UE) hoy en día incluye 27 países, 16 de los cuáles han formado la Unión Monetaria Europea (UME), y hay países como Islandia, Turquía o Croacia que han solicitado su incorporación. Sin embargo, el proceso de integración económica no estuvo y todavía hoy no está exento de problemas y temores. Antes y justo después del lanzamiento del Euro hubo mucha preocupación sobre posibles factores que pudiesen destruir la unión monetaria y un alto nivel de escepticismo sobre el éxito del Euro. Se creó un intenso debate sobre si el Euro introduciría más convergencia o divergencia en la evolución económica de los países. Por un lado, los más optimistas estaban convencidos de que una política monetaria única eliminaría las perturbaciones idiosincrásicas o específicas del país. Por otra parte, los escépticos del Euro encontraron que el creciente grado de integración económica a través de los menores costes de transacción, una regulación más harmonizada y una mayor movilidad de capital y trabajo inducirían mayor especialización. Esto implicaría que los países estarían más expuestos a perturbaciones especificas del país, dando como resultado mayores divergencias macroeconómicas. Además, el pacto de Estabilidad y Crecimiento limita el uso de la política fiscal. Esto junto con la cesión de los tipos de cambio y política monetaria a una autoridad supranacional podría hacer más difícil para los países acomodar las perturbaciones y, por consiguiente, acentúar las diferencias.

El principal coste de la integración monetaria es sacrificar la flexibilidad del tipo de cambio y la política monetaria como instrumentos de estabilización. Este coste puede llegar a ser especialmente severo en presencia de rigideces de precios y salarios y de perturbaciones asimétricas porque bajo tales condiciones, las economías tienen muy poco margen de maniobra para responder o acomodar dichas perturbaciones. El riesgo de perturbaciones asimétricas consiste en la posibilidad de que economías dentro del área monetaria experimenten perturbaciones distintas a las del resto de economías del área. O cabe la posibilidad que incluso sufriendo el mismo tipo de perturbaciones que las demás economías de la unión, su diferente estructura socioeconómica, mercado de trabajo, regulaciones, la importancia relativa de sectores industriales, financiero o bancario, etc, produzcan reacciones muy diversas en las economías de la unión.

Es muy difícil estimar la probabilidad de que se produzcan perturbaciones asimétricas en un área monetaria. Un modo de entender la importancia de estas perturbaciones asimétricas muy extendido en la literatura es estudiar cómo de similares son las fluctuaciones de la actividad económica en los diferentes países y regiones. Cuanto más parecidas sean, menores serán los costes de la integración. Típicamente, esta similitud se asocia con sincronía cíclica. Además, estudiar la evolución de la sincronía por países a lo largo tiempo es informativa de los efectos de la integración económica. Sin embargo, entender los determinantes de sincronización también contribuye a hacer inferencia sobre la evolución del proceso. Por ejemplo, las divergencias cíclicas se pueden explicar porque los países tengan diferentes patrones de especialización productiva que les lleven a enfrentarse a distintas condiciones de demanda y oferta.

La gran recesión de 2007-09 ha sido un ejemplo de una perturbación común con efectos asimétricos. Esta crisis ha mostrado que hay todavía importantes diferencias estructurales entre los miembros de la UE y que se necesitan todavía mecanismos para hacer frente a estas perturbaciones. Precisamente por esta razón también ha sido una alerta sobre la necesidad de ser cautelosos en relación a futuras nuevas ampliaciones. Por otra parte, la gran recesión también ha cambiado la tendencia de suavizamiento de los ciclos observada tanto en EE.UU. como en la mayoría de los países de la UE desde principios de 1980, fenómeno denominado gran moderación. Después de un largo periodo de estabilidad, ahora es más evidente que nunca que las relaciones entre los países y las variables económicas cambian en el tiempo y también a lo largo de las fases del ciclo. De hecho, se observa que la volatilidad de las variables macroeconómicas aumenta en los periodos recesivos y esto lleva consigo un aumento de las correlaciones, y este es uno de los principales motivos de que los modelos económicos, sobre todo los modelos factoriales, no fueran capaces de predecir la magnitud de la recesión.

Esta tesis tiene como objetivo estudiar las diferentes características de los ciclos económicos así como el grado de sincronía cíclica o comovimiento en los ciclos de los distintos países y regiones de la Unión Europea y algunos países avanzados así como sus determinantes. Además, se identifican varios hechos estilizados en relación a la varianza y las correlaciones de las variables macroeconómicas y el ciclo.

En este trabajo se trata pues de responder a las siguientes preguntas: ¿Están los países sincronizados cíclicamente? ¿Son las expansiones y recesiones muy parecidas por países? ¿Existe un ciclo Europeo? ¿Qué ha pasado con la sincronía y las características de los ciclos en los países Europeos desde que decidieron unir sus políticas? ¿Cuáles son los principales determinantes de la sincronía? ¿Por qué la mayoría de los modelos fallaron en predecir la gran recesión?

Metodología

Este trabajo utiliza un conjunto amplio y variado de técnicas econométricas e incluso propone mejoras o extensiones de técnicas existentes. Básicamente comprenden modelos de series temporales como Vectores Autorregresivos (VAR), estimaciones de espectros en el dominio de frecuencias, técnicas no-paramétricas para fechado de recesiones y expansiones, simulación bootstrap, técnicas de análisis multivariante como análisis de grupos (cluster) jerárquico y no jerárquico y escalado multidimensional, modelos de grupos basados en mixturas finitas, modelos de regresión lineal estimados por mínimos cuadrados ordinarios y por variables instrumentales, modelos factoriales dinámicos, técnicas de simulación como el método de Monte Carlo con cadenas de Markov (MCMC) o el método de simulación secuencial de Monte Carlo (SMC) junto con una diversa batería de tests estadísticos.

En cuanto a las mejoras propuestas, se propone un método para combinar correlaciones, un nuevo método estadístico para determinar o no la existencia de un ciclo Europeo, una mejora en el popular algoritmo de fechado de Bry-Boschan introduciendo bootstrap estacionario y una extensión del modelo factorial dinámico para que tenga en cuenta que los momentos de segundo orden (i.e. varianzas y correlaciones) son cambiantes.

En relación a los datos para el estudio, el principal indicador de ciclo considerado es el índice de producción industrial (IPI), mensual y ajustado de estacionalidad. Además, se consideran algunos indicadores macroeconómicos adicionales dependiendo del objetivo perseguido en cada capítulo referentes al comercio, política fiscal, productividad, precios, renta, empleo, etc. La muestra de países considerada engloba a la mayor parte de países de la UE-27 junto con otros países industrializados como EE.UU. El periodo considerado varía dependiendo del país.

Conclusiones y resultados

Las principales conclusiones de este trabajo son:

- Las divergencias cíclicas en términos de comovimiento entre los nuevos países miembros de la UE con los antiguos países miembros, y también entre ellos, son mucho más importantes que las diferencias que los antiguos países miembros tenían antes del establecimiento de la unión.
- En promedio las expansiones son más largas y más amplias que las recesiones. Aunque las recesiones en la mayoría de los países del este europeo son más profundas que en el resto. Las expansiones en general son convexas, esto es, empiezan dicha fase con crecimiento suave y la finalizan con crecimiento más fuerte. En relación a esto último, no se observa un patrón claro para las recesiones.

- Además, encuentro evidencia en contra de la existencia de un ciclo común europeo. En otras palabras, las economías europeas no están tan sincronizadas o no tienen ciclos cuya longitud, profundidad y forma sea tan parecida como para considerar que existe un ciclo representativo de toda la UE o de la UME.

- Se muestra evidencia de que los ciclos económicos apenas han cambiado con la unión monetaria puesto que la estabilidad del tipo de cambio no ha implicado una convergencia considerable ni en las características de los ciclos ni en la sincronía cíclica. De hecho, las economías parecen menos sincronizadas en los últimos quince años (hasta 2004). Sin embargo, el grado de asimetría cíclica se ha reducido en promedio. Por un lado, los ciclos en promedio desde los años ochenta son más suaves debido a la reducción de la amplitud de ambas fases del ciclo, lo que está en sintonía con la literatura sobre la reducción de volatilidad o gran moderación. Por otra parte, la forma de las expansiones ha pasado de ser cóncava a convexa, implicando que la fase de recuperación con rápido crecimiento ha desaparecido, y por ello ahora se observa que la fase expansiva comienza con recuperaciones muy suaves sin creación de empleo (jobless recoveries).

- Encuentro un papel para las diferentes variables macroeconómicas como factores explicativos de los comovimientos entre las economías. Además del comercio, hay una contribución significativa de otras variables macroeconómicas, estructurales y de política económica, tales como la especialización productiva, la productividad del trabajo o política fiscal, para explicar los comovimientos cíclicos. Estos resultados apuntan a la existencia de persistentes divergencias cíclicas y diferencias estructurales e institucionales (por ejemplo, en la productividad laboral) entre las economías europeas. Y ésto hace más probable que ocurran perturbaciones asimétricas o perturbaciones con efectos asimétricos y plantea dificultades para la toma de decisiones sobre la postura apropiada de política monetaria para acomodarlas.

- He extendido el modelo factorial dinámico estándar de una forma parsimoniosa para que recoja una serie de hechos estilizados en relación a las varianzas y las correlaciones. Adicionalmente, he propuesto una forma novedosa, fácil de implementar y apropiada para ejercicios de predicción, de introducir volatilidad estocástica en estos modelos basado en un método secuencial de Monte Carlo, el filtro de partículas. Este método es rápido, eficiente y robusto a no linealidades y ausencia de gaussianidad. Muestro que este modelo heteroscedástico tiene mejores propiedades predictivas a corto plazo, especialmente en momentos de elevada incertidumbre, y además, permite obtener la volatilidad del factor que podemos interpretar como un indicador de riesgo macroeconómico.

1. Introduction

More than 50 years ago six European countries - Belgium, France, Italy, Germany, Luxembourg and the Netherlands - decided to create the European Economic Community. It has been a long way since then and lots of progress was made in the economic integration. Indeed, the European Union (EU) nowadays includes 27 countries, 16 of which have formed the European Monetary Union (EMU), and there are countries like Iceland, Turkey or Croatia which have applied for membership. However, the process of economic integration was and still is not exempt from problems and fears. Before and just after the launch of the Euro there were many concerns about possible factors that could undermine the monetary union, and a high level of skepticism about the Euro success. There was an intense debate about if the Euro would induce more convergence or divergence in the economic performance across countries. On the one hand, the more optimistic were convinced that the single monetary policy would eliminate idiosyncratic or country-specific nominal shocks. On the other hand, the Euro sceptics found that the increased economic integration by means of the lower transaction costs, a more harmonized regulation and a higher mobility of capital and labor would induce more specialization. This would mean that countries are more exposed to country-specific shocks, giving as a result more macroeconomic divergences. Furthermore, the Stability and Growth Pact limits the use of fiscal policy. This together with the cession of the exchange rates and monetary policy to a supranational authority could make it more difficult for countries to accommodate shocks and thus enhance the divergences.

The relevant literature is large although far from consensual. Most of these works rely on the theory of Optimal Currency Areas (OCA) developed by Mundell (1961) and extended later on by McKinnon (1963) and Kenen (1969). Mundell pointed out some benefits and costs of constituting a monetary union. Regarding the benefits, there are important gains derived from abandoning the exchange rate flexibility such as the reduced uncertainty and transaction costs and the price transparency which together have a positive effect on trade, the improvements in the anti-inflationary reputation and the elimination of negative externalities with the coordinated monetary policy. The main cost is to sacrifice the exchange rate flexibility and the monetary policy as stabilizing tools. This cost will be especially severe in the presence of price and wages rigidities and asymmetric shocks because under these conditions it becomes harder for the single countries to accommodate them. To evaluate if the Euro area constitutes an OCA is to make a cost-benefit analysis, which will depend on to what extent European economies are likely to face asymmetric shocks. In principle, these are shocks or unexpected changes in the demand or the supply that affect one of the country members but not the rest of members. This was the approach followed in the very beginning. But then there were also concerns about the possibility of symmetric shocks with asymmetric effects. This means a common shock that affects the whole area but produces distinct reactions in the economies of the area due to the differences in socio-economic structure, labor market, regulations, etc. This is related to Walter's famous critique: "one size does not fit all". The effects of a symmetric shock can be asymmetric because the single monetary policy might not produce the desired effects in all countries and the national governments have available a narrower margin to operate.

It is very difficult to estimate how likely asymmetric shocks or symmetric shocks with asymmetric effects in a monetary union actually are. The literature on OCAs has proposed several criteria for optimality of a currency area. They are conditions under which the benefits exceed the costs or in other words, it is less likely that asymmetric shocks happen. Following Baldwin and Wyplosz (2006) these criteria are: i) labor mobility (Mundell, 1962); ii) diversification of the production (Kenen, 1969); iii) trade openess (McKinnon, 1963); iv) existence of fiscal transfers; v) similar tastes and preferences; vi) to share the vision of a common destiny. These criteria suggest that the more homogeneous or similar are the economies that get integrated, the lower the probability of asymmetric shocks will be. However, the picture is more complicated because, as Frankel and Rose (1998) argued, these criteria are endogenous. It could be that in the very beginning the countries that decide to get integrated do not fulfill the criteria and therefore do not constitute an OCA. But enjoying the benefits of the monetary union such as the positive trade effect can lead to a gradual change such that over time the area becomes an OCA.

One way to understand the importance of the asymmetric shocks which is very extended in the literature is to study how similar the fluctuations of the economic activity in the different countries or regions are. The more similar the fluctuations are, the lower the costs of the integration will be. Typically, this similarity is associated with synchronicity. Studying the synchronization across countries over time is informative about the effects of economic integration. However, it is also important to study the determinants of synchronization and the shape of the cycles. The diverging business cycles may be explained for instance by the different patterns of specialization that lead countries to face different demand or supply conditions.

The recent great recession was an example of a common shock with asymmetric effects. This crisis has shown that there are still important structural differences across members of the EU and that mechanisms are still needed to deal with asymmetric shocks or shocks with asymmetric effects. Indeed the design of the fiscal policy plays a crucial role and is one of the main challenges for the EMU and the EU. The crisis was also a warning about the need to be cautious about new future enlargements. However, for some European countries outside the Euro area it was clearer than ever during the crisis that if they had been members of the EMU, they would not have had to decide between cutting interest rates to avoid recession or raising them to stabilize the exchange rates[1].

This dissertation contributes to the literature on business cycle analysis with four essays. In the first essay I study the cyclical synchronization using several measures for robustness. The recent two enlargements of the European Union in 2004 and 2007 provide a larger sample of countries and make it possible to compare the old member countries of the EU and the EMU with the new members. I also consider other developed countries for comparison purposes and analyze how the cyclical comovement has evolved over time across countries of the EMU and in the EU to see if the economic integration has encouraged cyclical convergence.

In the second essay I study other important characteristics of the business cycles, in particular of their phases, expansions and recessions. One shortcoming of this approach is that it requires a dating of the phases and there exists no official chronology of recessions and expansions for the European countries. So, the characteristics are going to importantly depend on the dating procedure. Additionally, in most of the existing dating methods there are problems when the samples are short, when there are short-lived cycles and with the beginning and the end of the samples. I propose a novel method to overcome these common problems and obtain robust results.

In the third essay I identify the main factors that drive business cycle synchronization. Trade has had a positive effect on the cyclical synchronicity, but there are other important structural factors like the divergences in the patterns of specialization in production and the fiscal policy that could also be relevant.

The fourth essay has to do with how the Great Recession of 2007-09 has changed the observed trend of smoother cycles in the United States (US) (a phenomenon that was called the Great Moderation) and in most of the EU countries since the beginning of the 1980s. Now it is more evident that the relationships across countries and economic variables change over time, and also along the phases of the cycle. During the recessions the volatility of the macroeconomic variables increases reflecting a higher level of uncertainty or macroeconomic risk, and at the same time the correlations are higher. In this essay I focus on the US case, because I have available data since the post-war period and thus, a higher number of cycles. I identify several stylized facts regarding the variance and correlations (i.e. second order moments) of several macroeconomic variables. And I propose a parsimonious solution to account for these stylized facts and improve forecasting at the same time in a dynamic factor model.

[1]For a detailed discussion, see chapter 26 in Blanchard, Amighini and Giavazzi (2010).

2. Business Cycle Synchronization

2.1. Introduction

The academic literature and the press are full of references to the importance of globalization and the links across economies. Many works such as Gregory, Head and Raynauld (1997), Lumsdaine and Prasad (2003), and Canova, Ciccarelli, and Ortega (2006), talk about the *world business cycle* and, assuming since the very beginning that this cycle exists, estimate it and calculate its importance in explaining country specific movements. Many other papers focus on the *European business cycle*, also considering that there exist European specific business cycle driving forces or factors. Supporting this view, significant examples are Mansour (2003), Del Negro and Otrok (2003), Artis, Krozlig and Toro (2004), and all the literature behind the coincident indicator for the Euro area by Forni, Hallin, Lippi and Reichlin (2001).

The purpose of this chapter is to analyze the comovements across economies without previously making assumptions about whether or not they should move together. We want to let the data speak without imposing any kind of a priori restrictions. This approach makes it possible to draw a map of comovements across economies to check if they are close or, on the contrary, further away from each other. At the same time it answers the leading question about the existence of either a world or an European cycle. To that extent, this work makes different contributions to the literature. First, we propose a two-by-two comparison across economies without taking any of them as reference for the others. Second, we calculate several measures of comovements across economies for robustness purposes.

To deal with these questions, we concentrate on the western European economies, although we extend the usual European sample of countries in two different ways. On the one hand, this work includes a set of industrialized economies to understand how close or far the European economies are from other major industrialized countries. On the other hand, it also considers the eastern European economies that represent most of the recent enlargements of the European Union (EU). In this way we can address additional questions, key to measure the gains and costs of the current and future enlargements of the EU and the European Monetary Union (EMU).

When countries join a monetary union, they leave to a supranational decision-maker the traditional instruments for the control of the business cycles. The optimality of this delegation is a direct function of the similarities across these economies. If the economies move together, we might think that they need the same type of economic policy decisions at the same time. If there is no synchronization of their business cycle comovements, different solutions are optimal for different economies and the costs associated to an economic union might probably be higher than the gains.

On the other hand, all the literature about accession economies has to do with convergence criteria and convergence tests, as in Brada, Khutan and Zhou (2005). Other authors take as given a *leading* economy and analyze the transmission of shocks from this economy to the accession economies, as in Boone and Maurel (2002). However, we do not find in any paper a careful analysis of the comovements of each of the accession economies with each of the European and other major industrialized economies. With this European focus in mind, there are additional economic questions to address. For example, so far the western European economies linked their policies without any major trauma in their economies. But was the economic integration of these economies not traumatic because these economies had previous linkages? Have these economies increased their comovements since they decided to join their policies? Is there a country that acts like an "attractor" or leading economy? Is there a limit to the expansion of the EU? To answer these questions it is necessary to understand the benefits and the costs for the different economies of the economic integration. The chapter is structured as follows. Section 2 characterizes the concept of business cycles synchronization and checks whether the economies move together and how far these economies are from each other. Section 3 analyzes the existence of a common attractor or leader among European economies. Section 4 uses multivariate analysis techniques to identify clusters among the European and non-European economies. Section 5 concludes.

2.2. What is business cycle synchronization?

2.2.1. Data

In the business cycle analysis we use the monthly industrial production (IP) index (seasonally adjusted) as an indicator of the general economic activity. This choice has the drawback that it measures only one sector and only the supply side of the economy. However, after several attempts with different indicators, we find this option the most convincing. Indeed we firstly constructed a diffusion index for each economy using the approach of Stock and Watson (2002) but due to the few series available for the accession economies this approach was not very promising. Then, we also computed a composite index for each country with the Kalman filter using a small and simple dynamic factor model as in Stock and Watson (1991), with the series of industrial production, total sales, employment and a measure of income for the different economies. However, this specification gave in many cases a weight close to one to the IP series and almost zero to the others. And finally, we also considered a more comprehensive measure of the aggregate activity using the gross domestic product (GDP). However, this series is quarterly instead of monthly, and the available samples are shorter. Furthermore, for most of the European countries the GDP is not calculated from national accounts on a quarterly basis. Instead it is converted from annual to quarterly series using indicators. We therefore concluded that IP is the most suitable series for our objective.

The sample of the countries include all the European Union countries prior to the enlargements of 2004 and 2007: Belgium (BG), Denmark (DK), France (FR), Germany (BD), Greece (GR), Ireland (IR), Italy (IT), Luxembourg (LX), Netherlands (NL), Portugal (PT), Spain (ES), United Kingdom (UK), Austria (OE), Finland (FN) and Sweden (SD); all the accession countries but Malta and Bulgaria: Cyprus (CY), Estonia (ET), Latvia (LA), Lithuania (LI), Poland (PO), Slovakia (SK), Slovenia (SL), the Czech Republic (CZ), Hungary (HN) and Romania (RO); and one negotiating country: Turkey (TK). Finally, we also include some industrialized countries: Canada (CN), the United States (US), Norway (NW) and Japan (JP). The source of the data is the OECD Main Economic Indicators and the IMF International Financial Statistics. In the analysis of European and industrialized countries we use data from 1965.01 to 2003.01. The exercises including the accession countries use data from 1990.01[1].

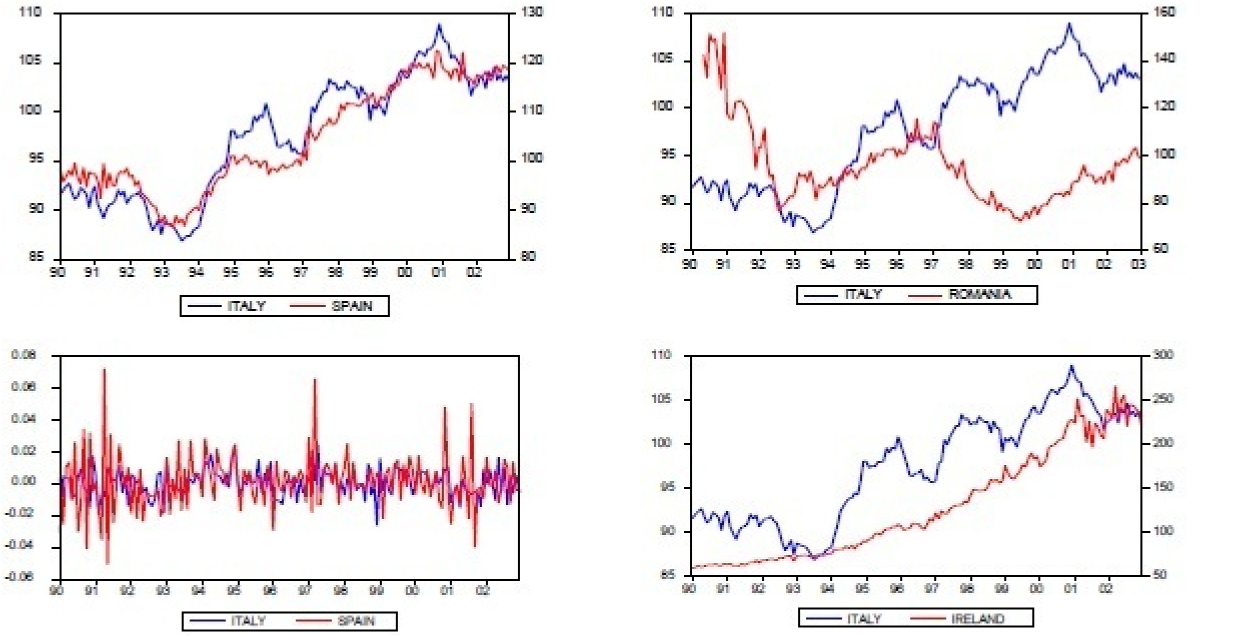
2.2.2. Correlation as a measure of comovement

The typical measure of business cycle comovement or synchronization is the correlation. But it is not exempt from problems that the next graphs help to illustrate. Figure 2.1 plots the IP series of Italy, Spain, Romania and Ireland as well as the first difference of the logs of the IP series of Italy and Spain. Looking at the pictures in levels, it seems that the IP of some, but not all, of these countries move together. A first glance to the picture would say that Italy and Spain (both Mediterranean countries) present synchronized business cycles so that they should not have major problems linking their economies. In contrast, in the case of Italy and Romania, or Italy and Ireland, the synchronization of their IP does not seem to be so evident, so that joining these economies with a supranational decision-maker should reduce the optimality of the stabilization policies for at least one of the economies.

This figure also poses an additional question. When calculating correlations the choice between using the levels (or log-levels) or the rates of growth is not obvious. For example, using the IP of Italy and Spain, the correlation between the log-levels is 0.94 whereas the correlation between their growth rates is 0.09. Hence, the log levels of the series show that the comovements of the series are very important, while the first differences lead to the opposite conclusion. To illustrate this puzzling result

[1]Even though for most of the accession countries the statistical information is available since 1990, we do not use the first two years of observations because according to Blanchard (2003) or the World Bank (2002) the atypical falls in output during the transition period are not conventional recessions.

Figure 2.1.: A first graphical approach



Note: The top left figure plots the levels of the Industrial Production series for Italy and Spain and the top right, for Italy and Romania. The bottom left figure represents the rates of growth of the Industrial Production for Italy and Spain, and the bottom right the levels for Italy and Ireland.

we propose the following example. Let us assume that the data generating process for the series x_t and y_t is

$$x_t = a + x_{t-1} + \phi(y_{t-1} - y_{t-2}) + e_t \tag{2.1}$$

$$y_t = b + y_{t-1} + u_t \tag{2.2}$$

with serially uncorrelated errors, $e_t \backsim N(0, \sigma_e^2)$, $u_t \backsim N(0, \sigma_u^2)$, and with $E(e_t, u_t) = 0$. Finally, we assume that both x_1 and y_1 are zero. Under these assumptions the correlation between the series in log-levels is

$$corr(x_t, y_t) = corr\left((a + \phi b)(t-1) + \phi \sum_{j=1}^{t-1} u_j + \sum_{i=2}^{t} e_i, b(t-1) + y_{t-1} + \sum_{j=2}^{t} u_j\right) \tag{2.3}$$

which tends to one because the trend effect dominates. However, the correlation between the first differences of the log-levels is

$$corr(x_t - x_{t-1}, y_t - y_{t-1}) = corr\left(a + \phi(b + u_{t-1}) + e_t, b + u_t\right) \tag{2.4}$$

which is close to zero. This example illustrates the general problem in defining the correlation as a measure of business cycle comovements: when using series in levels or log-levels the long-term component dominates the correlation, and when using the first differences of the logs the short-term noise dominates the correlation. Thus, what is necessary is a kind of filtering (more sophisticated that just taking the differences) to extract the information of the series about the short-term movements (and comovements) of the series. The chosen filter affects the shape of the cycle, and, of course, the comovements. Therefore, we propose three different measures of comovements for robustness of the results. The first measure is based on VAR estimations following Den Haan (2000); the second one relies on spectral analysis and follows Croux et al. (2001); and the last one is based on the business cycle dummy variables approach of Harding and Pagan (2006).

2.2.2.1. Measure 1: VAR-based approach

Den Haan (2000) argues that unconditional correlation coefficients lose important information about the dynamic aspects of the comovement across variables. And in the case of non-stationary variables (as the ones in the previous example), the unconditional correlation produces spurious estimates. To solve these problems he uses the correlations of the VAR forecast errors at different horizons as a measure of comovement of the series. He proposes the following identification scheme:

$$Z_t = \mu + \sum_{j=1}^{p} A_j Z_{t-j} + \varepsilon_t \tag{2.5}$$

where Z_t represents in our case the differences of the logs of IP indexes for each pair of countries at time t, A_j is a (2×2) matrix of regression coefficients, μ is a vector of constants, p is the number of necessary lags, and ε_t are serially uncorrelated errors with zero mean and covariance matrix Ω[2]. Out of this specification, the k-period ahead forecast error is

$$Z_{t+k} - Z_{t+k|t} = \sum_{j=0}^{k-1} \Theta_j \varepsilon_{t+k-j} \tag{2.6}$$

[2]Den Haan specifies a more general model with linear and quadratic deterministic trends. In our case, for the sample considered these trends were not necessary for most of the countries. Furthermore, he shows that the results are robust to estimating the model in levels and in first differences. We present the results of the estimation in first differences but the results using the levels are very similar.

where $Z_{t+k|t}$ is the k-period ahead forecast, and Θ_j may be obtained recursively from $\Theta_j = \sum_{i=1}^{N} A_i \Theta'_{j-i}$, with $\Theta_0 = I$, and $\Theta_{\tau=0}$ for any $\tau < 0$. Therefore, the covariance matrix of this k-period ahead forecast error $Z_{t+k|t} = Z_{t+k} - Z_{t+k|t}$ becomes

$$E\left(Z_{t+k|t} Z'_{t+k|t}\right) = \sum_{j=0}^{k-1} \Theta_j \Omega \Theta'_j \tag{2.7}$$

Finally, the correlation between the k-period ahead forecast error between the two variables that form Z_t will be the element (2,1) of the previous matrix divided by the product of the two forecasted standard deviations for the two series (elements (1,1) and (2,2) of the previous matrix).

The empirical results are presented in the end of this section, but here we make some clarifications. The results are presented in terms of distances instead of correlations to facilitate comparisons. The distances are defined as one minus the value of the correlations. In this way when the correlation between two countries is near one because their cycles are very synchronized, the distance is close to zero. On the contrary, when the correlation is around zero, the distance is close to one. The distances vis-à-vis computed from the correlation of 48-month ahead (i.e. a horizon of 4 years) forecast errors are in Table A.1 of Appendix A.

2.2.2.2. Measure 2: spectral-based approach

In the spectral analysis the time series can be expressed as the sum of infinite sinusoidal functions or waves with different frequencies and amplitudes. This is the *spectral decomposition* of the time series and makes it possible to disaggregate time series into components of distinct periodicities. The study of business cycles is based on the components with periodicities ranging from 1.5 to 8 years or, in terms of frequencies, from 0.07 to 0.35 radians. The spectral and cross-spectral density functions are tools to investigate the explanatory power of each component in the behavior of the original series. The spectral density is a function that decomposes the variance of variable x_t across intervals of frequencies ω and it has this form,

$$S_x(\omega) = \frac{1}{2\pi} \sum_{h=-\infty}^{\infty} e^{-ih\omega} \gamma_x(h) = \frac{\gamma_x(e^{i\omega})}{2\pi} \tag{2.8}$$

where $\gamma_x(h)$ is the auto-covariance function, $\omega \in [-\pi, \pi]$, and $\gamma_x(e^{i\omega})$ is the auto-covariance generating function. In the bivariate case the spectral function is known as the cross-spectral density function, and it decomposes the covariance between two variables across different frequencies,

$$S_{x,y}(\omega) = \frac{1}{2\pi} \sum_{h=-\infty}^{\infty} e^{-ih\omega} \gamma_{x,y}(h) = \frac{\gamma_{x,y}(e^{i\omega})}{2\pi} \tag{2.9}$$

where $\gamma_{x,y}(h)$ is the cross-covariance function, $\omega \in [-\pi, \pi]$, and $\gamma_{x,y}(e^{i\omega})$ is the cross-covariance generating function. The correlations in the frequency domain are obtained from these decompositions of variance and covariance in the frequency band of the business cycle. In this work the chosen measure of correlation is the *dynamic correlation* defined by Croux et al. (2001):

$$\rho_{x,y}(\omega) = \frac{real(S_{x,y}(\omega))}{\sqrt{S_x(\omega)S_y(\omega)}} \tag{2.10}$$

The main advantage of this measure is that it is a real number, taking values between -1 and 1, and also incorporating the sign of the relation. In this way it overcomes some problems of other measures used in the literature such as the coherency, that can take imaginary values, and the squared coherence, that does not keep the sign of the relation.

To conclude the explanation, we make some final remarks concerning the estimation of the spectrum. First, Granger and Hatanaka (1964) showed that the spectral and cross-spectral methods applied to non-stationary series should be used with caution, since the variance of these series tends to infinity, and the spectrum is in this case an approximation (pseudo-spectrum). Therefore, it is preferable to first apply a transformation to obtain a stationary series. For instance, one can use some filter to reduce or eliminate the lower frequencies of the series before estimating the spectrum. In this work we have used the first differences of the logs of series, even though it introduces distortions at high frequencies leaving the remaining frequencies almost unaltered. We could have chosen a different filter instead, such as the Band Pass filter (Baxter and King, 1999) or the popular Hodrick-Prescott filter (Hodrick and Prescott, 1997), but there were several reasons that persuaded us not to do it. The Band Pass filter has to be applied to stationary data, so it is compulsory to take the first differences before using it and also to truncate the filter. Regarding the Hodrick-Prescott filter, several papers have found that it could lead to spurious results[3]. Second, to overcome the asymptotic inconsistency of the estimates, we use the standard Barlett's lag spectral window. And third, we truncate the sum with a truncation parameter equal to the sample size to the power of one third[4], because otherwise it is impossible to calculate the sum of infinite terms. The results of the pairwise distances are displayed in Table A.2 in Appendix A.

[3]See Jaeger, 1994 and Cogley and Nason, 1995 among others.

[4]Either if the truncation parameter M tends to infinite or it is a function of the sample size T, the asymptotic unbiasedness is guaranteed independently of the lag window function used (see Priestley, 1981). On the other hand, Andrews (1991) proposed using $M = O(T^{1/3})$ for the Bartlett window. In our work we used values from 3 to 6, according to the formula $M = T^{1/3}$.

2.2.2.3. Measure 3: Dummy-based approach

The third approach to assess the degree of synchronicity among the countries' business cycles is based on Harding and Pagan (2006). They consider the pairwise correlation coefficient among their "reference cycles" or a binary variable taking value one when the country is in recession and zero otherwise[5]. Unfortunately, with the exception of the US economy, for which the National Bureau of Economic Research (NBER) dates its official peaks and troughs, no generally accepted reference cycle is available for the other countries. In this work we follow the well-known procedure of Bry and Boschan (1971) to identify the countries' business cycle turning points[6]. These authors developed an algorithm to isolate the local minima and maxima in a series, subject to reasonable constraints on both the length and the amplitude of the expansions and contractions. Table A.5 in Appendix A shows the chronology of expansions and recessions as the result of applying this dating procedure to the thirty IP series. Notice that the identified turning points for the US are either identical or close to the official NBER turning points[7]. Having a look at these tables, it is easy to anticipate two conclusions about the business cycle synchronization. First, as noted by Massmann and Mitchel (2003), the timing of the European business cycle phases is more synchronous during the period before 1990 than in the period after this date. For example, all of the countries that experienced the first recession of the seventies showed the peak in 1974. However, it does not happen with the first recession of the nineties which starts in a range from 1989 to 1992 depending on the country. Second, the synchronization between European and accession countries is rather limited. While more than 80% of the European countries experienced the first recession of the new century, this percentage is less than 40% for the group of accession countries.

Harding and Pagan measured the degree of business cycles synchronicity between country i and country j with the sample correlation between their reference cycles. A simple way to obtain this measure is by the regression

$$\sigma_i^{-1} D_{it} = a_{ij} + \rho_{ij} \sigma_j^{-1} D_{jt} + u_t \tag{2.11}$$

where D_i is the reference cycle of country i, σ_i is its standard deviation, and most importantly, ρ_{ij} is the sample correlation between the reference cycle of countries i and j. The pairwise distances are collected in Table A.3 in Appendix A.

[5] These authors show the advantages of using the correlation index instead of the concordance index of Artis and Zhang (1997, 1999) to analyze business cycle synchronicity.

[6] Several authors propose slightly different versions of the Bry-Boschan dating rule. In this respect, Garnier (2003) finds that they lead to similar turning points for most of the industrialized countries.

[7] One noticeable exception is the peak in the last eighties. This seems to be a characteristic of nonparametric dating rules based on industrial production indexes, as documented by Artis, Kontolemis and Osborn (1997) and Garnier (2003).

Harding and Pagan propose a simple test of the null of no business cycle synchronization, or a zero correlation coefficient, by using the t-ratios and allowing for heteroskedasticity and serial correlation. However, we think that this test may be biased to reject the null of no correlation simply because there are more zeroes than ones in the countries' reference cycles since expansions are typically longer than recessions. In this respect, we propose a new approach to develop the test of no business cycle synchronization between countries i and j based on the bootstrap approximation of the t-ratio's true distribution. First, we compute the countries' reference cycles D_{it} using the Bry-Boschan dating procedure. Second, for each country we estimate the probability of being in recession, the probability of being in expansion, and the probability of switching the business cycles phase. Third, given these estimates, we generate 10,000 reference cycle variables sharing the same business cycles characteristics than these two countries. Finally, we compute the p-value associated to the null of zero correlation coefficient.

2.2.3. Empirical results

Before discussing the results, it is important to make some clarifications. The distances for pairs of countries are in Tables A.1 to A.3 in Appendix A. However, in this subsection we are going to refer to average values of the correlations (and distances) to facilitate the comparisons. Notice that the correlation between two variables in a sample is not the average correlation of the sub-samples. Therefore, for instance, the correlation across the Euro area economies is not the average of the correlations between each pair of countries. There is one transformation in the statistical literature, the *inverse hyperbolic tangent* $\tanh^{-1}(\bullet)$, that is useful to combine several correlation coefficients and obtain a statistic with a known distribution for the correlation. It consists in transforming the correlation coefficient r in this way

$$\zeta = \tanh^{-1}(r) = 0.5(\ln(1+r) - \ln(1-r)) \tag{2.12}$$

so that ζ is normally distributed, with mean r and variance $1/T$, where T is the sample size. This transformation is also called the Fisher's z-transformation (David, 1949).

To combine different correlation coefficients, for instance r_1 and r_2 computed over samples of sizes T_1 and T_2, the coefficient that summarizes both may be calculated using the Fisher transformation as

$$\zeta' = \frac{1}{T_1 + T_2}(T_1 \tanh^{-1}(r_1) + T_2 \tanh^{-1}(r_2)) \tag{2.13}$$

that is normally distributed with variance $1/(T_1+T_2)$. And then, we undo the transformation to obtain a correlation coefficient which summarizes both $r = tanh(\zeta')$ and is more suitable to combine correlations than a simple average.

2.2.3.1. Measures of business cycle synchronization

Table 2.1 shows a summary of the distances (i.e. one minus the correlation coefficient) computed from the IP series since the nineties. The first measure shows that the EMU-12 economies are more interlinked across them than with the accession economies (distances of 0.61 versus 0.82). In fact, if we test the null hypothesis of no correlation against the alternative of positive correlation, the results in Table 2.2 show that the null is rejected in more than 50% of the occasions in the case of Euro countries among themselves, but only in 27% in the case of accession countries among themselves[8]. However, according to this measure, this link is previous to the creation of the Eurozone (the distance computed from series since the sixties to the eighties is 0.56, and the null of no correlation is rejected in 73% of cases).

Table 2.1.: Summary of distances across economies

	1990.01-2003.01		1961.01-1989.12
	EMU-12	Accession	EMU-12
Measure 1			
EMU-12	0.61 (0.06)	0.83 (0.05)	0.56 (0.04)
Accession	-	0.82 (0.04)	-
Measure 2			
EMU-12	0.55 (0.06)	0.70 (0.06)	0.44 (0.05)
Accession	-	0.66 (0.05)	-
Measure 3			
EMU-12	0.70 (0.05)	0.93 (0.05)	0.65 (0.04)
Accession	-	0.73 (0.04)	-
Comprehensive			
EMU-12	0.62 (0.06)	0.82 (0.05)	0.55 (0.05)
Accession	-	0.73 (0.04)	-

Note: Values in parenthesis are the p-values.

The dynamic correlations based on the second measure confirm the previous results. The EMU-12 countries are closer than accession countries (distances of 0.67 versus 0.84). Besides, if we test the null hypothesis of no correlation against the alternative of positive correlation, we reject the null in more than 65% of the occasions in the case of Euro countries among themselves, and 45% in the case of accession countries

[8] We have bootstrapped the VAR forecasts errors for different forecast horizons. With this distribution, we are able to calculate a 90% confidence interval for each correlation coefficient.

among themselves[9]. And, with respect to the EMU-12 countries, this link is also previous to the creation of the monetary union (distance of 0.64 since the sixties to the eighties, and 83% of rejections of the null of no correlation among Euro countries).

Table 2.2.: Percentage of rejections of the null hypothesis of no correlation

	1990.01-2003.01		1961.01-1989.12
	EMU-12	Accession	EMU-12
Measure 1			
EMU-12	59.1%	28.8%	72.3%
Accession	-	27.3%	-
Measure 2			
EMU-12	65.1%	46.2%	83.3%
Accession	-	45.4%	-
Measure 3			
EMU-12	46.2%	9.8%	52.2%
Accession	-	27.3%	-

In relation to the third measure, the distance across EMU-12 economies has not decreased with the monetary integration. At the same time, as in the other previous measures, distances across Euro economies are slightly smaller than distances across accession economies (0.7 versus 0.75). Although in the last case, the big distances from accession countries to the EMU-12 countries (0.93) are remarkable. The results of applying our proposed test show that the correlation has decreased since the 1960s in the Euro area. The percentage of rejections of the null of no correlation is 52% since the sixties, becoming 46% in the nineties. As detected by Garnier (2003), the business cycle phases in the EMU-12 countries have become more idiosyncratic. At the same time, the correlation across accession countries is smaller than across EMU-12 countries (46% of rejections of the Euro versus 27% of the accession countries) and the same happens with the average rejection in the correlation between Euro and accession countries (9.8%).

Table 2.3.: Evolution of distances across EMU-12 economies

	1962.01-1975.12	1976.01-1989.12	1990.01-2003.01
Measure 1	0.53 (0.06)	0.77 (0.05)	0.61 (0.06)
Measure 2	0.25 (0.11)	0.66 (0.05)	0.55 (0.06)
Measure 3	0.57 (0.06)	0.67 (0.05)	0.70 (0.05)
Comprehensive	0.42 (0.08)	0.68 (0.05)	0.62 (0.06)

Note: Values in parenthesis are the p-values.

[9] We use the Fisher transformation and the delta method to obtain the standard errors of the correlation coefficients.

Finally, it is arguable that the results regarding the evolution of distances over time in the Euro economies may be biased because we are comparing two sub-samples of different sizes. For robustness check, we divided the first part of the sample into two shorter sub-samples of similar lengths: 1962.01-1975.12 and 1976.01-1989-12. The results in Table 2.3 reveal that the comovements across European economies were high in the 1960s and beginning of the 1970s. But then they decreased in the 1980s since most of these countries were hit by strong shocks. And they recovered in the 1990s, but without reaching the strong correlation of the 1960s. The conclusion is that although the monetary integration may have helped to create some links across its members, the effect in the business cycle synchronization is rather small.

2.2.3.2. A comprehensive measure

As a result from the previous subsections we have a collection of distances between countries, based on three different methodologies to measure the degree of business cycle synchronization among several European and non-European countries. However, in spite of the heterogeneity of the approaches, they come to the same two conclusions: synchronization between EMU-12 countries with themselves is higher than synchronization between accession countries with themselves, and there are no appreciable gains in synchronization between EMU countries in the last decade.

As frequently stated in the literature, a mixing of techniques should give more robust results than individual measures by themselves. Therefore, we again use the Fisher transformation to combine them and form a comprehensive measure of distance[10]. Following this strategy, Table A.4 in Appendix A displays all distances across all the economies. We also summarize these combined distances in the bottom of Table 2.1.

Table 2.4.: Statistical tests for the distribution of distances. P-values

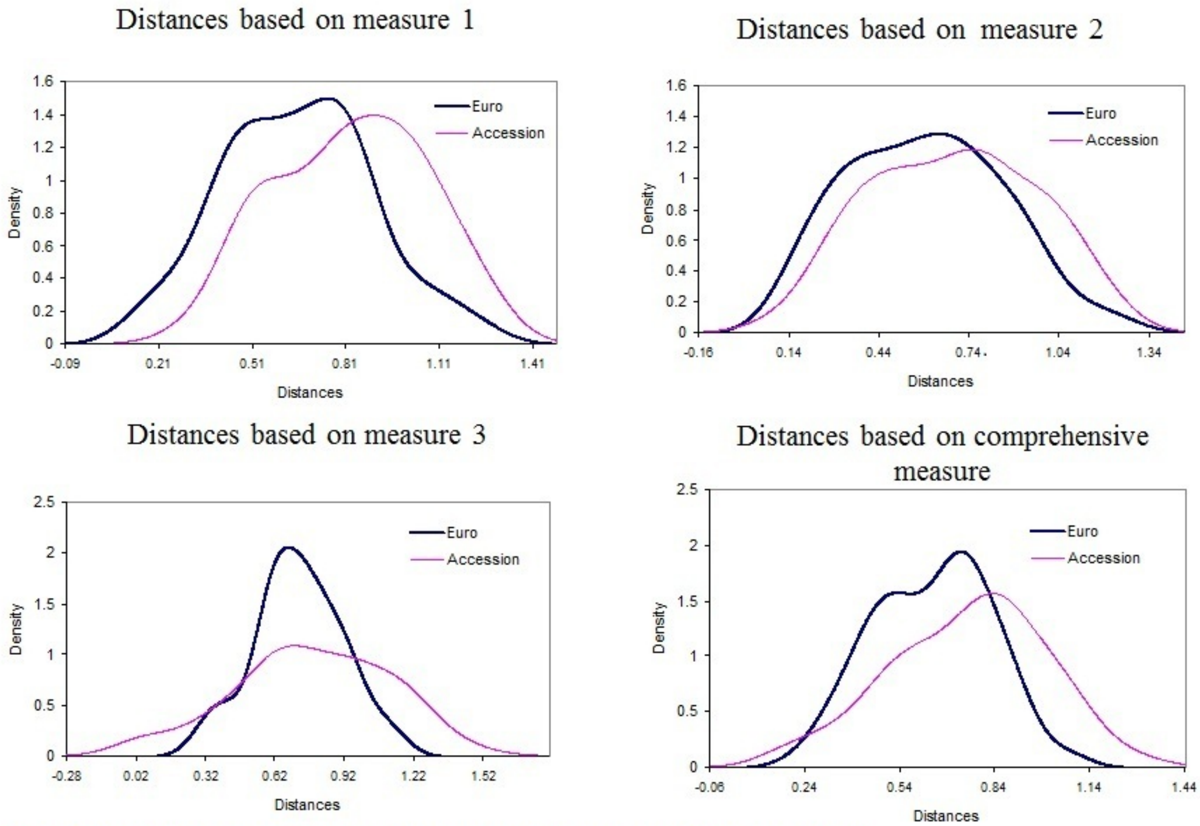
	EMU-12 vs Accession	
	Equal means	Equal variances
Measure 1	0.01	0.90
Measure 2	0.03	0.68
Measure 3	0.12	0.00
Comprehensive	0.01	0.02

Figure 2.2 plots the distributions of distances for the EMU-12 countries with themselves and the accession countries with themselves and leads to the conclusion that the EMU-12 economies seem to be more homogeneous and closer together than the accession countries. Furthermore, Table 2.4 shows the p-values for the statistical

[10] Alternatively we could think of ways to give more weight to some measures. However, it is worth mentioning that potential ways of weighting, as for example giving more weight to the measure with less dispersion, do not help in this case because the standard error of the distribution of distances for each measure is the same.

tests of the null hypothesis that the means and the variances of the distances across the EMU-12 and accession economies are equal. Both hypothesis are clearly rejected for the comprehensive measure. Nevertheless, notice that the variance of the distances in the first and second measure for the Euro area members is higher than in the third and comprehensive measures. For this reason the null hypothesis of equal variances is not rejected for measures 1 and 2.

Figure 2.2.: Distribution of the distances: EMU-12 vs Accession countries



Note: The density functions have been approximated using the Silverman's kernel estimation procedure.

Table A.6 in Appendix A provides supplementary information about the distances of each country with each group of countries: EMU-12, EU-15, industrialized economies, and the accession countries. For the EU-15 countries, Norway, Canada, Japan and the US it also displays these distances for the sample since the sixties to the eighties. What is remarkable is the big contrast between the distances of each individual country with the accession countries and with the other groups of countries considered. Another interesting result is that for most of the EU-15 countries the distances with the EMU-12, EU-15 and the industrialized countries have not changed much over time.

2.3. Multidimensional Scaling and Cluster analysis

In this section we explore the combined distances by using multidimensional scaling techniques to represent distance measures among objects on a plane (such as in a map), and cluster analysis techniques to classify objects into groups. The former is concerned with the geometric representation whereas the latter deals with the group identification.

2.3.1. Multidimensional Scaling

The purpose of Multidimensional Scaling (MDS) techniques (Cox and Cox, 1994) is to find a low dimensional coordinate system to represent n-dimensional objects and create a map of lower dimension ($k < n$) which gives approximate distances among objects. The k-dimensional coordinates of the projection of any two objects, r and s, are computed by minimizing a measure of the squared sum of divergences between the true distances $d_{r,s}$ and the approximate distances $\hat{d_{r,s}}$ among these objects[11]. Formally,

$$min_{\hat{d_{r,s}}} \frac{\sum_{r,s}(d_{r,s} - \hat{d_{r,s}})}{\sum_{r,s} d_{r,s}^2} \tag{2.14}$$

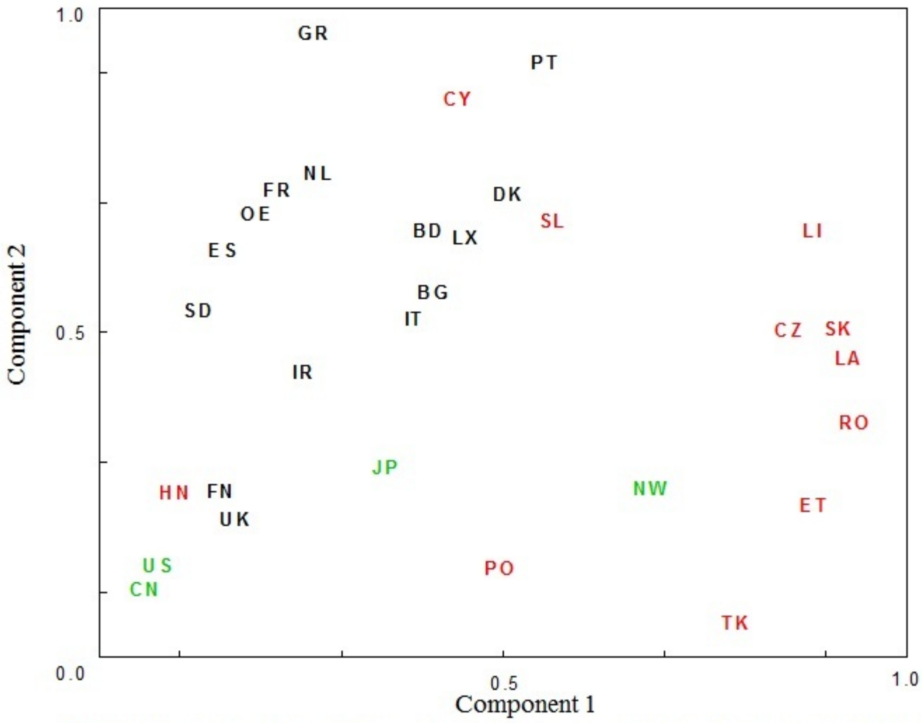
with

$$\hat{d_{r,s}} = (\parallel z_r - z_s \parallel^2)^{1/2} = \left[\sum_{i=1}^{k}(z_{ri} - z_{si})^2\right]^{1/2} \tag{2.15}$$

where z_r and z_s are the k-dimensional projection of the objects r and s, and z_{ri} and z_{si} are the k dimensions of each object. Notice that MDS is equivalent to using k principal components[12]. In the case of 2-dimensional representations, the resulting picture is much easier to interpret than distances in higher dimensional spaces as it is possible to represent the distances in a plane. In the resulting map, countries with big dissimilarities are represented in the plane far away from each other. Figure 2.3 plots the map of the comprehensive measure of distances (i.e. the combination of the distances among countries obtained with the three approaches) using MDS. This representation provides a glimpse of how close the cycles among countries are. For example, the cycles in the United Kingdom are closer to those of Canada and the United States than to the EMU-12 countries. And the EMU-12 countries are closer to each other than to any other group of countries. On the other hand, the accession countries are far from each other.

[11] This measure is usually called the Standardized Residual Sum of Square (STRESS).
[12] We refer the reader to Kruskal (1964) and Timm (2002) for more details.

Figure 2.3.: Map of averaged business cycles distances



Note: This map is the multidimensional scaling map based on the averaged distances of the business cycles.

2.3.2. Cluster analysis of the business cycle synchronization

In this subsection, we identify clusters of countries according to their business cycle synchronization. Countries in the same cluster have a higher synchronization across them than countries in other groups. Typically the cluster analysis is performed in two steps. In the first step the number of clusters is determined using the hierarchical clustering algorithms (i.e. explanatory method). Given the number of clusters obtained, the second step consists in applying non-hierarchical clustering or partitioning algorithms (i.e. confirmatory method) to find the optimal partition. Next we give some insights about these two steps[13].

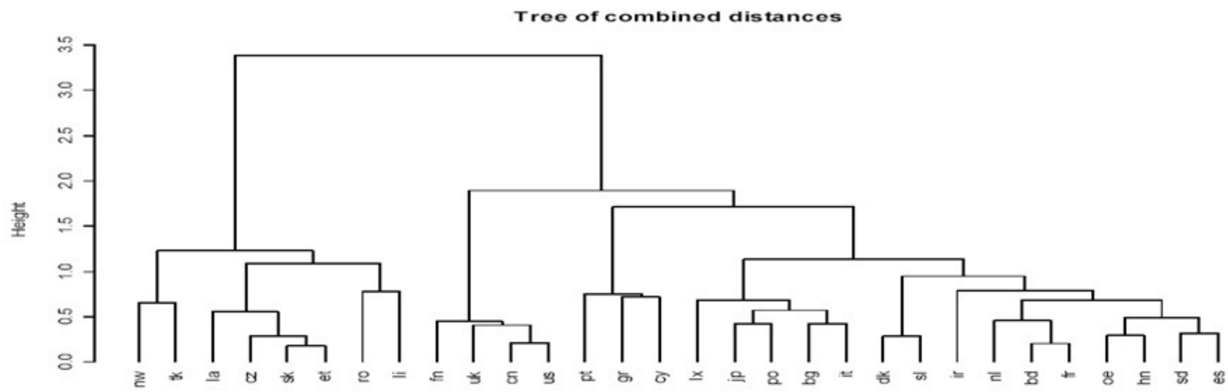
1st step: Hierarchical clustering. The hierarchical algorithms are used to generate groups from a set of individual items. The algorithms begin with each item forming its own cluster. And after that the clusters are iteratively combined with the two most similar clusters according to some criteria[14] until all of them

[13]For more details, see chapter 9 in Timm (2002).

[14]We use the most similar criterion of Ward (1963) that is based on the minimal increment of within-group sum of squares. In practice, suppose that there is a cluster p formed by countries r and s, and we are interested in computing this criterion to see whether country q joins group p or not. According to this criterion the distance between cluster p and country q is:

form a single cluster. The plot of this sequence of cluster solutions is a tree diagram or *dendrogram*. The tree starts with the leaves at the bottom where the original items are situated. Then, the pair with the lowest distance forms the first group. In the following steps, the items or clusters are successively combined, forming the branches of the tree until reaching the top of the graph. The height of the tree represents the level of dissimilarity at which observations or clusters are merged. The higher the height of the tree, the more dissimilar are the observations contained in the clusters. A big inter-group dissimilarity involves a great jump to join two groups and it means that the optimal number of groups is often situated at those junctures.

Figure 2.4.: Dendrogram



Note: The dendrogram's height represents the level of dissimilarity at which observations or clusters are merged.

Figure 2.4 shows the dendrogram for our set of distances among countries. This algorithm joins items and forms clusters based upon minimizing the increase in the sum of squares of distances within clusters[15]. Looking at the figure, we can observe big jumps in forming two, three and four groups. We do not have a clear tool to decide the optimal number of groups, so that in the next step we try these three options. However, just looking at the tree, we can observe a group formed by most

$$d_{p,q} = \frac{n_r + n_q}{n_p + n_q} d_{r,q} + \frac{n_s + n_q}{n_p + n_q} d_{s,q} - \frac{n_q}{n_p + n_q} d_{r,s}$$

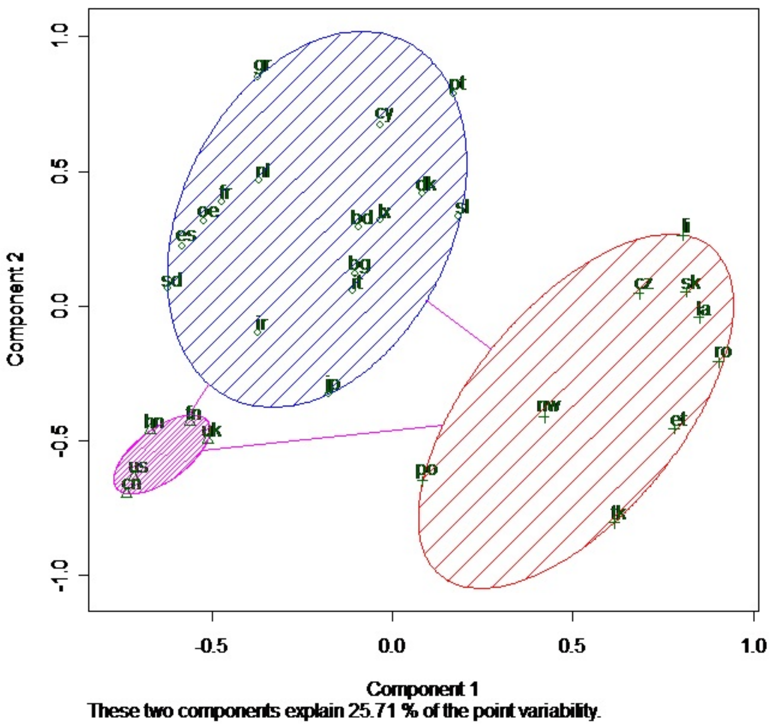
where $d_{r,s}$, $d_{s,q}$ and $d_{r,q}$are the distances between countries r, s and q, and n_r, n_s, n_p and n_q are the number of countries included in each cluster. Notice that if the cluster is formed by a single country, as for instance country q, n_q is one.

[15]For robustness, we tried two other criteria, the average link and complete link methods, leading to similar results.

of the EU countries, another group formed by the US and related economies (such as Canada or the United Kingdom), a third group with most of the accession countries, and a fourth group with three countries (Cyprus, Greece and Portugal) exhibiting very atypical business cycles in comparison to the other countries.

2nd step: Non-hierarchical clustering. These algorithms seek the optimal partition or composition of the clusters. It is optimal in the sense that the objects of the same cluster should be close to each other, whereas the objects of different clusters should be far away. They classify the data into k groups, given a priori by the user, satisfying the requirements that each group must contain at least one object and that each object must belong to exactly one group. These methods are usually called partitioning methods since they make a clear-cut decision and there are different approaches depending on the optimality criterion. In this work we follow the k-medoid method following Kaufman and Rousseeuw (1990)[16].

Figure 2.5.: Map with clusters



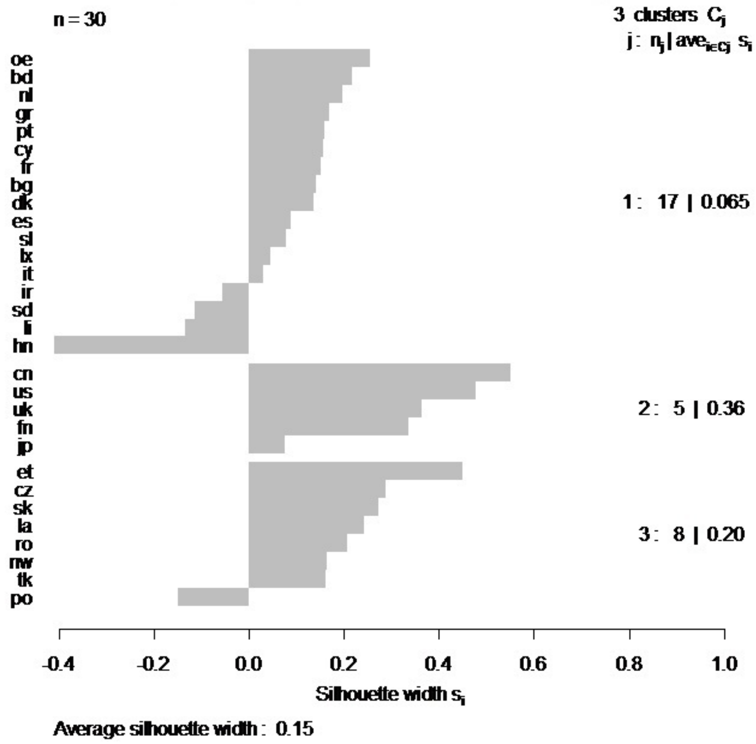
In the previous step we concluded that there may be between two and four clusters of countries. Hence, our analysis starts considering four groups. The fact that one cluster includes countries with atypical behavior implies that when searching for the

[16]These authors show the advantages of the k-medoid method of Vinod (1969) with respect to other approaches as the k-means method of McQueen (1967).

optimal composition of those four groups, these atypicals do not form a group but are distributed into the other groups. This is because the distance across them is too big to link themselves together. On the other hand, upon imposing only two groups, one of the resulting groups is too big because it consists of the atypical countries, all the EU countries, the US and related economies, with very high heterogeneity across them. Therefore, we think it is preferable to estimate three groups.

Figure 2.5 displays the resulting clusters from the k-medoid method when imposing three groups. We obtained the following groups: i) the first cluster includes the EMU-12 economies (except Finland), Denmark, Sweden, Cyprus, Lithuania, Slovenia and Hungary; ii) the second cluster includes the US and other industrialized economies as Canada, the United Kingdom, Japan and Finland. iii) The third cluster is the cluster of accession countries: Latvia, Estonia, Slovakia, Czech Republic, Romania, and Poland, but also Turkey and Norway.

Figure 2.6.: Silhouette plot



However, the interpretation of the results must be made carefully. Even though we plot three groups, the average similarities between groups are very small in all cases. We computed the silhouette width (Rousseeuw, 1987), a measure of cohesion within a cluster with respect to the neighbor clusters. A value close to one means that countries are well clustered whereas a small coefficient means poor clustering structure. The silhouette widths are displayed in Figure 2.6. Notice that each cluster has an average silhouette width value between 0.1 and 0.3. Special mention deserves the case of Hungary with a high negative value for its silhouette width suggesting that the methodology has difficulties to assign this economy to any of the existing groups.

2.4. Is there a common European cycle?

The previous results may be erroneously interpreted as in favor of those papers that consider the existence of a core among the European business cycles. Most of the papers cited in the introduction, when dealing with the problem of the European business cycle comovements, consider a business cycle attractor that is usually either a leading economy or a weighted average of all the economies of the area. In this section we study whether there is one country or groups of countries in our sample that act as an attractor. This would mean that there is a cycle that we could identify as the “European cycle”. The question is if those points (countries) in the map of Figure 2.3 or Figure 2.5 are randomly distributed or whether there is any kind of attractor that keep them together. To answer this question we propose a new methodology that, to our knowledge, has not been used in the literature before. The idea is that if there exist an attractor, most of the distances between the leading country and the rest of countries would be small, and we would observe a great amount of small distances and very few large ones.

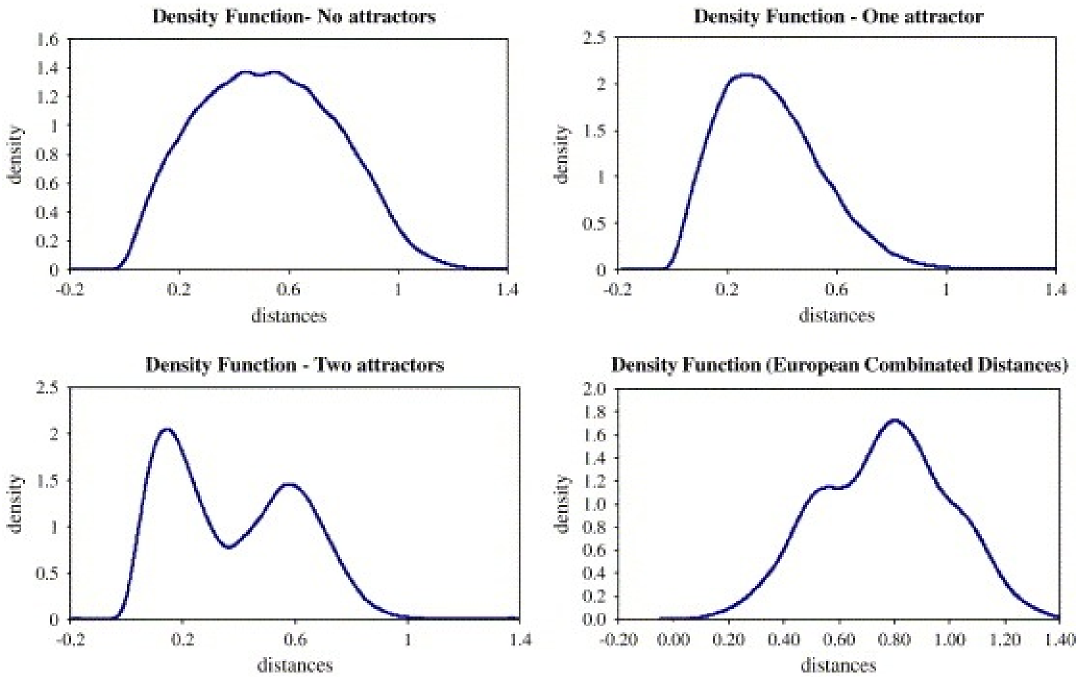
We develop the analysis by using the following exercise. First, we normalize the distances to include them in a square of dimensions 1x1. Second, we generate 27 observations (30 countries minus Japan, the US and Canada) from a bivariate uniform distribution and we calculate the distances between each pair of points[17]. We repeat this exercise 10,000 times and generate the density function of those distances between each pair of points (top left panel of Figure 2.7). The plotted distribution represents the distances across points when there is no attractor across them since they have been generated by a uniform distribution[18]. Third, we generate 27 observations with the same support space but coming from a bivariate normal distribution, where an attractor is clear. We repeat the exercise 10,000 times and show the distribution of the distances (top right panel of Figure 2.7). As we can see, in the case of one attractor, there is a concentration of small distances across the points, implying a higher value for the skewness than in the case of the uniform distribution. Additionally, we consider the possibility of the existence of two attractors. In order to simulate economies with two attractors we consider a mixture of

[17]For this exercise, we consider all the European economies in order to maximize the number of observations used for the kernel density estimation.

[18]The plot represents the density function of the distances across the 27 points, generated 10,000 times. The density function has been approximated with a kernel estimator following Silverman (1986).

bivariate normals with a probability for mixing of 0.5. If this is the data generating process and the distances between the two attractors are big enough, we will expect a bimodal distribution as the one plotted in the bottom left panel of Figure 2.7. We have generated the plot by extracting 10,000 times observations from a mixture of normals. The bimodality comes from the fact that there is a set of short distances associated with observations that are generated by the same normal and a set of long distances associated with observations that have been extracted from different normals.

Figure 2.7.: Distributions of the points based on simulated and observed distances



Note: The density functions have been approximated using the Silverman's kernel estimation procedure.

In the bottom right panel of Figure 2.7 we represent the distribution of the distances[19] of the actual data. There are a few basic statistics that help us to distinguish which is the distribution that describes better the data generating process of the observations: i) Skewness: High values of the skewness imply evidence for the existence of one attractor; ii) Bimodality index[20]: It is defined by $BM = (m_3^2 + 1)/[m_4 + 3(n-1)^2/(n-2)(n-3)]$ where m_3 is the skewness coefficient, m_4 is the kurtosis coefficient, and n is the number of observations. Values of this index greater than 0.55 provide evidence in favor of a bimodal pattern or the existence of two attractors.Table 2.5 presents the basic statistics of the different distributions of the simulated and observed data. Even though we concentrate our

[19]The results shown are based on the comprehensive measure of distance. The results with the other three measures are similar but are not included for brevity reasons.

[20]See Timm (2002), pag. 535.

explanation on the combined measure of distance, the results are extremely robust to any of the three other measures, as shown in Table 2.5. We can observe that the estimated skewness of the observed data is -0.08, which is statistically different than the estimated value for one attractor, 0.65 (p-value of equality of the coefficients is 0.00) but not different from the value estimated for the uniform, 0.20 (p-value of 0.15). With respect to the existence of two attractors, the bimodality index of the data is 0.41, below the critical value of 0.55. However, the hypothesis of two attractors implies an estimated modality index of 0.59.

We have also performed the same exercise for the countries of the EU-15 and the EMU-12. Although in Table 2.5 are only shown the statistics for the observed data, the exercise followed the same steps as before. The estimated skewness coefficients are 0.05 and 0.15, clearly lower than the skewness of one attractor and with p-values of 0.00 in both cases. The bimodality index of the data are 0.41 and 0.43, respectively, clearly below the critical value of 0.55.

In summary, in this section we have obtained no evidence for the existence of one or two attractors in the comovements across either the European economies, the EU-15 and the EMU-12 countries, and in all cases the null hypothesis of no attractor cannot be rejected.

Table 2.5.: Testing the existence of attractors. Key statistics

	Skewness	Kurtosis	Bimodality index
SIMULATIONS			
No attractor	0.20	-0.68	0.44
One attractor	0.65	0.26	0.42
Two attractors	0.19	-1.19	0.59
OBSERVED			
27 countries			
Comprehensive measure	-0.08	-0.56	0.41
Measure 1	-0.15	-0.44	0.40
Measure 2	0.24	-0.41	0.40
Measure 3	-0.16	-0.45	0.40
EU-15 countries			
Comprehensive measure	-0.05	-0.64	0.41
EMU-12 countries			
Comprehensive measure	-0.15	-0.75	0.43

2.5. Conclusion

Many works that analyze international links among economies usually assume that there is an European business cycle. This cycle is usually associated to some economies with a leading role in the area. The present work goes further by testing if such attractor or common business cycle actually exists without making assumptions. It also presents a comprehensive methodology to characterize the comovements across the economies. Moreover, a new method to test for statistical support of the supposed attractor is proposed. Using this test, we do not find statistical evidence for the existence of either one or two attractors in the comovements across the European, the EU-15 and EMU-12 economies. Obviously, this result puts a question mark on those works that either implicitly or explicitly assume that it exists. With the incorporation in 2004 and 2007 of twelve new members to the European Union, we think that the analysis of similitudes and differences among the actual members and the newcomers is very relevant. And in this work we show that the distances across the EMU-12 economies are more closely linked than distances across accession countries. But also that the accession countries are on average further away from the EMU-12 countries than across themselves. In relation to the evolution of the business cycle synchronization, in agreement with the results of Stock and Watson (2003), we show that the international economies seem to be less, rather than more, synchronized in the last fifteen years.

3. Characteristics of the Business Cycle

3.1. Introduction

In the literature of optimal currency areas, it is well known that joining a union does not necessarily imply an improvement for each of its members. The main cost of joining the union has to do with leaving the traditional economic stabilization policies to supranational authorities. The theoretical argument behind this reasoning is that stabilization decisions made at supranational levels could be optimal for the subset of countries with more homogeneous cycles but that they may be against the economic interest of countries with more atypical cycles. In the case of the European Union (EU), most of its members have left monetary decisions to the European Central Bank. Even for those countries that do not belong to the European Monetary Union (EMU), fiscal policies are restricted to the achievement of close-to-balance budget constraints that are imposed by the stability pact. In this context, a growing attention is being devoted to examine similarities and differences among the EU countries' business cycles. Remarkably, the majority of empirical studies has almost exclusively focused on synchronization or comovement business cycle dynamics. According to these studies, more synchronized countries are expected to face smaller costs of joining the Union than those countries with relatively less synchronized cycles. Among many others, recent academic examples are the studies of Dueker and Wesche (2003), Darvas and Szapary (2008), and the survey of de Haan, Inklaar and Jong-A-Pin (2008). In addition, relevant policymakers as Trichet (2001) when describing the increasing integration of European markets, only consider synchronization (correlation) to examine the degree of business cycle similarities. The attention to analyze similarities and differences in business cycle characteristics other than synchronization has been minor and mainly based on the description of some features of the cycle[1]. However, we consider that the evaluation of business cycle synchronization might be complemented with a careful analysis of the form of the cycles. Although synchronization of national business cycles is relevant to analyze the timing of stabilization policies, having synchronized cycles is a necessary but not

[1] We are aware of only two exceptions. Artis, Marcellino and Proietti (2005) study the business cycle characteristics of countries acceding the EU in 2004 using a different methodological approach. Krolzig and Toro (2005) simulate their estimated models for some EU countries to examine the characteristics of their estimated models.

sufficient condition to conclude that countries will exhibit low stabilization costs of joining the Union. For instance, within the existing literature on business cycle synchronization, countries with synchronized cycles do not face apparent costs of joining the Union in terms of their stabilization policies. However, if the shapes of their cycles are different, supranational policy reactions against recessions may be too accommodative for countries that change the business cycle phases sharply and too tight for countries whose state changes are smooth. These reactions may also last too long for countries with shorter duration of cycles and too short for countries with longer cycles. Finally, the strength of common stabilization policies may be insufficient for those countries with deeper cycles and disproportionate for countries with mild cycles. In this chapter we are going to offer a comprehensive framework to analyze business cycle characteristics other than synchronization. For this purpose, several statistical advances achieved in other areas have been adapted to the analysis of business cycles. On the one hand, we adapt the stationary bootstrap method proposed by Politis and Romano (1994) to the analysis of the business cycle characteristics that are described in Harding and Pagan (2002a). In our opinion, this method can be used to overcome several criticisms that the studies on business cycle characteristics have received in the past. In particular, the method reduces the dependence of the business cycle results to the existence of short-lived business cycle phases when analyzing short time series. On the other hand, we innovate in the statistical approach that has been used to compare business cycle characteristics of different countries. For this purpose, we employ the model-based clustering method outlined in Fraley and Raftery (2002) to group countries in several clusters with similar business cycles characteristics. In the empirical part, we compare the business cycle characteristics of the countries that have joined the EU in 2004 and 2007 with those of the old members. This comparison is important since the new members are encouraged to qualify for participation in the Monetary Union. In addition, we address the question of whether the European business cycles are similar enough to consider that there exists one European cycle with differentiated business cycle characteristics. The chapter is structured as follows. Section 2 presents the methodology that we follow to analyze the business cycle characteristics. Section 3 describes the data, characterizes the business cycles of our sample of countries and how they have changed over time, and studies the existence of an European cycle. Section 4 concludes.

3.2. Methodology to analyze business cycle characteristics

In this study we focus on classical business cycles, as in Harding and Pagan (2002a), to avoid the problem of detrending the series that we would have if we considered growth cycle. However, all the analysis could easily be extended to consider other definitions of cycle. This section attempts to construct the statistical framework to analyze characteristics of the EU countries' business cycles. First, we select the appropriate set of features that we need to obtain a detailed description of the form of their cycles. Second, due to the potential dependence of the results to the turning points dates, we offer a robust method to obtain business cycle characteristics from time series. Finally, we describe a statistical framework to group related countries in clusters with similar business cycle characteristics.

3.2.1. The key features to describe the business cycle

The empirical literature on business cycles has identified a wide variety of business cycle characteristics. Among them, we want to select the minimum set of features being able to provide a complete description of the business cycle from a series of production. The work of Burns and Mitchell (1947) was one of the first attempts to establish a definition of business cycle. These are some of the statements: *"Business cycles are a type of fluctuations found in the aggregate economic activity of nations that organize their work mainly in business enterprises: a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions and revivals that merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic. In durations business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar character with amplitude approximating their own*". We can see that Burns and Mitchell's classical description of business cycles reveals two key characteristics of the cycle: duration and amplitude.

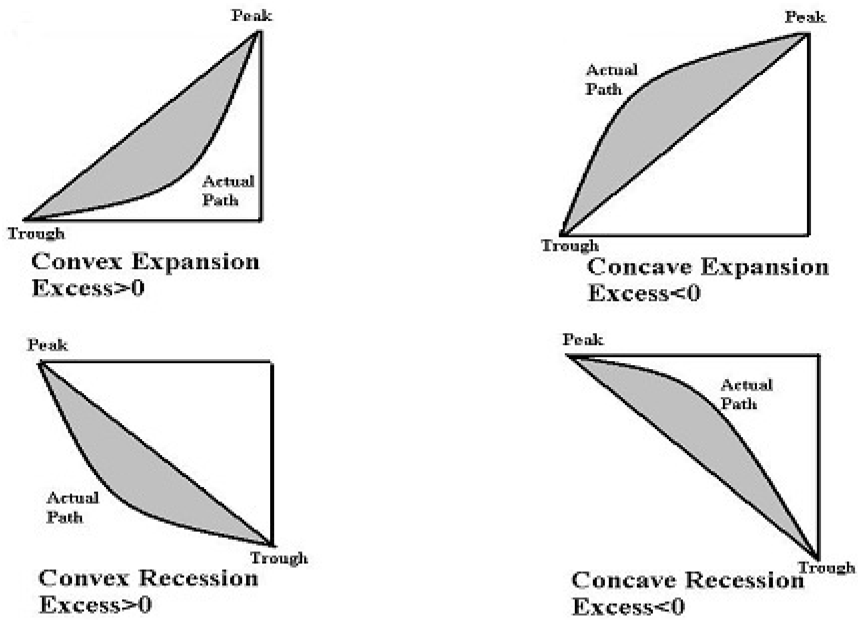
However, Harding and Pagan (2002a) consider three relevant business cycle features, length, depth, and shape, that are approximated by their measures of duration, amplitude, and excess, respectively. With respect to the length of the cycles, Harding and Pagan consider that the duration of an expansion corresponds to the time spent between the trough, that is the lowest level of activity and marks the end of a recession, and the following peak, that is the highest point of activity and marks the end of an expansion. Similarly, the duration of a recession is the time spent between a peak and the following trough.

In order to measure the depth of business cycle phases, we compare the log level of the time series at two consecutive turning points. In the case of expansions, one hundred times the amplitude represents the percentage that has been gained in terms of production. Alternatively, the amplitude may be interpreted as the percentage that have been lost in the case of recessions.

The last key dimension of the business cycle appearance is the shape. To consider this feature, the authors define a measure, called *excess*, that measures the departures of the actual time series path from the hypothetical path if the transition between two consecutive turning points was linear[2]. Defined in this way, the excess becomes an intuitive approximation to the second derivative of the series and

[2]For a given phase of the cycle, i, let C_i, C_{T_i}, and A_i be the actual cumulative movements

Figure 3.1.: Stylized representation of typical expansions and recessions



allows us to examine the concavity or convexity of the business cycle phase. To illustrate the relation between the sign of the excess and the shape of the cycle, Figure 3.1 depicts the stylized pictures of typical expansions (top charts) and recessions (bottom charts). Convex (concave) actual paths are characterized by positive (negative) slopes and positive (negative) measures of excess, that are represented by the shaded areas[3]. From another point of view, the excess may be related to the degree of abruptness with which the time series enters to and exits from the recessions or the expansions. In convex expansions and concave recessions, actual paths exhibit gradual changes in the slope at the beginning of the phase, but they become abrupt as the end of the phase comes. On the contrary, in concave expansions and convex recessions, actual paths start the phase of the cycle with steep changes and end smoothly.

of the series, the triangular approximation to the cumulative movements, and the amplitude, respectively. We compute the excess as the averaged values of $C_{T_i} - C_i + 0.5A_i$, where the last term removes the bias that arises in using a sum of rectangles to approximate the area under the actual path. Harding and Pagan (2002a) use the same measure but divided by the duration. We prefer to use our definition just to isolate the effect of the measure of the shape from the possible error of the duration measure.

[3]Note that Harding and Pagan (2002a) define excess as the area of the triangle minus the area of actual (see page 370) but they find an excess for expansions of 1.1. They interpret this positive value as evidence of the rapid recovery exhibited after recessions. However, rapid recovery with this definition in mind would mean negative excess for the expansions. We keep their formal definition, that coincides with their interpretation for the recessions but our sign is changed for the expansion periods.

3.2.2. Dating turning points and business cycle analysis

In empirical applications, it is worth noting that all of the previous measures of business cycle characteristics rely on having the appropriate turning point chronologies for each country. In the US, the National Bureau of Economic Research (NBER) Business Cycle Dating Committee has dated the expansions and recessions and its decisions have been generally recognized as the official business cycle dates. On the contrary, there is no widely accepted business cycle reference chronologies in other countries. Dating the turning points in countries other than US has been the source of many initiatives, that can be broadly classified as nonparametric and parametric.

Inside the nonparametric alternatives, the most popular one has been suggested by Bry and Boschan (1979). They develop an algorithm that isolates the local minima and maxima in time series, subject to reasonable constraints on both length and amplitude of expansions and contractions[4]. Among other authors, Harding and Pagan (2002b), and Artis, Marcellino, and Proietti (2004) have suggested alternative refinements of the Bry-Boschan seminal dating algorithm.

On the other hand, dating turning points through parametric models has gained considerable attention during the last fifteen years. Among the set of parametric specifications, the most widely used method to establish the different phases of business cycles has been the Markov switching specification of Hamilton (1989). However, other alternatives as the threshold autoregressive process of Tsay (1989), and the smooth transition autoregressive model of Teräsvirta (1994) have also been employed[5].

Choosing a method among these proposals does not seem to be an easy task as none of them is exempt from problems[6]. In any case, the dating methods usually face a high degree of uncertainty surrounding the signal estimates of some turning points. This leads different methods to provide the researchers with similar but not coincident business cycle chronologies. As it turns out, the results of the business cycle study may rely on subtle decisions about the dating mechanism adopted in the analysis. Examples of this inconsistency can be found all over in the literature. One significant example is Krozlig and Toro (2005) who find conflicting business cycle chronologies for Italy from Markov switching and nonparametric dating methods, especially at identifying the two recessions for the nineties. Another example is the different business cycle chronologies from Artis et al. (2005) and the chronologies we obtained in Chapter 2 (Table A.5 in Appendix A) that come almost entirely from refinements to the Bry-Boschan method applied by the former authors. Most of

[4]For example, they enforce minimum lengths of expansions and recessions, and ensure that peaks and troughs alternate.

[5]For a comprehensive coverage on parametric techniques in business cycle identification see Camacho and Perez-Quiros (2002).

[6]Nonparametric models have been criticized for using ad-hoc dating rules. Parametric models have the inconvenience of making all the business cycle analysis to rely on the underlying model's assumptions.

the differences among the business cycle chronologies that are obtained from these methodologies are associated to the existence of the so-called mild recessions. If our interest is just on synchronization, the question of including or not mild recessions in the final business cycle chronologies will probably lead to negligible effects in the analysis of synchronization since they are very short-lived. Even if our interest is on other business cycle characteristics, the effects of including mild recessions will be averaged out over the large set of business cycles that comes from large time series. However, including a mild recession in the middle of an expansion in short time series will lead to considerable changes in the analysis of business cycle characteristics. The problem is aggravated by using standard dating methods since they typically lose a valuable amount of information in the tails of the time series as they are not able to locate the first and last turning points. All of these problems are embedded in the analyzes that include time series for the recently acceded countries that typically contain at most two or three complete cycles. For all of these reasons, the studies of business cycle characteristics have been very dependent on the particular dating method used in these analyses. This dependence and the associated lack of robustness of the results have probably been the main drawback that diminishes the impact of the papers that analyze the characteristics of the business cycle.

3.2.2.1. A robust dating method based on Stationary Bootstrap

To overcome the previous drawbacks, a reasonable solution may be found in bootstrapping the original series. In our case, the bootstrap procedure should be based on moving blocks bootstraps since they involve resampling methods to form pseudo-time series that retain the autocorrelation structure of the original data. Among the several methods developed for time series, we use the stationary bootstrap resampling scheme of Politis and Romano (1994) since this method is relatively less sensitive to the choice of the block length than other standard moving blocks bootstrap methods[7]. The implementation of this method consists on bootstrapping blocks of the original data in which the first observation in each block is sampled from a discrete uniform distribution on $\{1, ..., T\}$, where T is the sample size. The block length, l, is randomly sampled from a geometric distribution, whose density function is

$$P(l = k) = (1 - p)p^{k-1} \tag{3.1}$$

for $k = 1, 2, ...$, and some $p \in [0, 1]$, that refers to the probability of incorporating one observation to the block. In this case, the expected size of each block is then

[7]These authors show that the stationary bootstrap method leads to consistency and weak convergence of the resampling.

given by

$$E(l) = (1 - p)^{-1} \tag{3.2}$$

In short, the proposed way of using stationary bootstrap to compute the business cycle characteristics consists in generating 10,000 bootstrapped time series from the original data. Each of these series comes from a concatenation of blocks of random size l. Then we apply the Bry-Boschan algorithm to compute their respective 10,000 business cycle turning points chronologies[8]. Each of them serves the basis for calculating one point estimate of the empirical distribution of the business cycle features that we have previously selected to describe the business cycle. Final business cycle characteristics are computed by averaging from their empirical distributions. This method mitigates the problem of the dating of recessions with short time series with just a few full cycles observed. From the bootstrapped series, we generate thousands of full cycles for which we can estimate the proposed business cycle characteristics and their standard errors. Additionally, we solve the problem of the effect of mild business cycle phases. The reason is that, although the dating algorithm may produce atypical characteristics due to the existence of mild business cycle phases, they are expected to be averaged out by bootstrapping if they are not part of the data generating process. In addition, the valuable information that is associated to the beginning and to the end of the time series will be included in the stationary bootstrap analysis. Let us examine with an illustrative example the validity of the stationary bootstrap method in the analysis of business cycle characteristics.

To start with, we generate ten different time series of 200 observations from the same data generating process that is supposed to follow a Markov switching as in Hamilton (1989). In order to provide the data generating process with economic meaning, we impose the generated data to have similar expected business cycle properties to those that we observe the data. For this purpose, we first apply the Bry-Boschan algorithm to our sample of countries and compute the within expansions and within recessions averaged values of duration (41 and 14 months), amplitude (15% and -12%), means (0.005 and -0.007), and standard deviation (0.001). The averaged estimates of the probabilities of staying in expansions and recessions is 0.976 and 0.940, respectively. Finally, we simplify the experiment by considering that the data generating process is linear in both phases of the cycle which leads to measures of excess equal to zero. The expected business cycle characteristics of these generated series are presented in the first row of Table 3.1.

[8] Among the nonparametric dating methods, we select the Bry-Boschan algorithm since it is the easiest way to search turning points in our large set of replications.

Table 3.1.: Simulation exercise

	Expansions			Recessions		
	Duration	Amplitude	Excess	Duration	Amplitude	Excess
Expected value	41	0.15	0	17	-0.12	0
Simulated						
1	30.25	0.15	-0.18	19.75	-0.13	-0.11
2	25.50	0.13	-0.04	24.50	-0.16	0.02
3	37.67	0.16	-0.46	43.50	-0.29	0.09
4	73	0.35	-0.56	18	-0.12	-0.01
5	95.50	0.45	2.21	9	-0.07	-0.01
6	51	0.23	0.59	15.67	-0.10	-0.04
7	45.67	0.23	-0.08	31.50	-0.20	-0.43
8	53	0.25	0.04	13.67	-0.10	-0.01
9	52.5	0.26	0.04	31.67	-0.21	0
10	60	0.26	-0.04	20	-0.14	-0.04
Min	25.5	0.13	-0.56	9	-0.29	-0.43
Max	95.5	0.45	2.21	43.50	-0.07	0.09
Range	70	0.32	2.77	34.50	-0.21	0.52
Average	52.41	0.25	0.15	22.73	-0.15	-0.05
Bootstrapping						
1	31.43	0.15	0.02	17.35	-0.12	0.01
2	28.66	0.14	-0.02	23.05	-0.14	-0.01
3	30.70	0.14	-0.04	31.66	-0.20	0.02
4	43.19	0.20	-0.04	14.67	-0.10	0
5	57.93	0.28	0	8.92	-0.07	-0.01
6	45.10	0.20	0.20	11.37	-0.07	-0.01
7	37.95	0.18	0.02	24.64	-0.15	-0.17
8	39.72	0.18	0.02	14.42	-0.09	-0.02
9	35.48	0.17	0.02	26.21	-0.18	-0.05
10	48.59	0.20	0.25	16.37	-0.11	-0.03
Min	28.66	0.14	-0.04	8.92	-0.20	-0.17
Max	57.93	0.28	0.25	31.66	-0.07	0.02
Range	29.27	0.14	0.29	22.74	0.13	0.20
Average	39.87	0.18	0.04	18.66	-0.12	-0.03

We first proceed to date the turning points of the ten generated series by means of the Bry-Boschan algorithm and then, to obtain duration, amplitude and excess of the identified recessions and expansions. Their resulting business cycle characteristics are shown at the top of Table 3.1. Although the ten time series have been generated from the same data generating process, there are considerable differences among their business cycle characteristics. The ranges of variation of these characteristics are usually larger than twice their expected values, leading in some cases to business cycle characteristics that clearly misrepresent the actual characteristics of the data generating process. For example, in the fifth generated series expansions are much longer, deeper and sharper, and recessions are much shorter and smoother than in the rest of the generated samples and than in the data generating process.

This example illustrates that the high degree of uncertainty associated to some turning points obtained with dating algorithms may lead the results on business cycle characteristics to be highly imprecise.

Let us now move to the stationary bootstrap results. For each of the ten generated samples, we compute 10,000 bootstrapped time series by resampling blocks of expected length of 41 months ($p = 0.976$) since this is the mean duration of expansions in our sample of countries[9]. The resulting averaged business cycle characteristics are displayed at the bottom of Table 3.1. The dispersion of the business cycle characteristics has dramatically reduced, and the averaged values for all the ten generated series are much closer to their expected values than in the case of computing these characteristics with the standard method. It is worth noting that the bootstrapped characteristics sometimes coincide with their expected values. These results confirm the usefulness of the stationary bootstrap method to compute robust business cycles characteristics[10].

3.2.3. Grouping countries with similar characteristics

In order to provide a complete framework to analyze business cycle characteristics, it is useful to consider a principled statistical approach that allows us to summarize results. For this purpose, we adopt the model-based clustering using finite mixture models approach described by Fraley and Raftery (2002). Using this method we can group countries with similar characteristics, and test whether these countries exhibit business cycle characteristics similar enough to consider one cycle with similar characteristics for all of them. To outline the strategy of clustering based on mixture models, let us consider that the population of interest may consist of G different sub-populations. Given a sample of N countries, let us collect the d business cycle characteristics of any country n in the d-dimensional vector x_n[11]. Assume that each observation is a sample drawn from a probability distribution with joint density:

$$f(x|\tau_g, \mu_g, \Sigma_g) = \sum_{g=1}^{G} \tau_g \Phi(x|\mu_g, \Sigma_g) \tag{3.3}$$

[9]In the empirical analysis, we show that our results are robust to reasonable values of the expected block sizes.

[10]We know that, since our method keeps the autocorrelation structure of the original data, it may be influenced by historically exceptional events affecting short time series. If the data generating process changes over time, the results may depend on the sample period chosen although they will still be robust to the dating method employed in the analysis.

[11]In our case, we consider six business cycle characteristics that correspond to duration, amplitude and excess for expansions and recessions, respectively.

where the τ_g's are the mixing proportions, with $\tau_g \geq 0$, and $\sum_{g=1}^{G} \tau_g = 1$, and $\Phi(x|\mu_g, \Sigma_g)$ is the p-dimensional Gaussian density, with μ_g and Σ_g being its mean vector and covariance matrix, respectively. The goal of the mixture maximum likelihood method is to find the parameters τ_g, μ_g, and Σ_g, collected in τ, μ, and Σ, that maximize the likelihood:

$$L(\tau, \mu, \Sigma) = \Pi_{n=1}^{N} f(x_n|\tau_g, \mu_g, \Sigma_g) \tag{3.4}$$

As the authors describe, the parameter estimates may be found through the expectation-maximization (EM) algorithm (Dempster et al. 1977), that is a general approach to maximum likelihood in the presence of incomplete data. This algorithm initializes with an initial guess of z_{ng}, the posterior probabilities that country n belongs to cluster g, given the maximum likelihood estimates τ, μ, and Σ. On the one hand, the M-step, consists on estimating the mixing proportions and means from the simple closed forms,$\tau_g = \frac{n_g}{N}$, and $\mu_g = \frac{1}{n_g} \sum_{n=1}^{N} z_{ng} x_n$, with $n_g = \sum_{n=1}^{N} z_{ng}$. These authors show that the geometric properties (volume, shape and orientation) are governed by the covariances Σ_g. In particular, they propose a parametrization of the variances in terms of its eigenvalue decomposition:

$$\Sigma_g = \lambda_g D_g A_g D_g' \tag{3.5}$$

The parameter λ_g governs the volume of the cluster. The matrix A_g is a diagonal matrix such that $|A_g| = 1$ with the normalized eigenvalues of Σ_g in decreasing order, and determines its shape. Finally, the matrix D_g is formed by the eigenvectors of Σ_g and determines its orientation. Due to the reduced number of sample observations, in this paper we assume that the clusters are spherical but have different volumes, that is $\Sigma_g = \lambda_g I$, where

$$\lambda_g = \frac{1}{pn_g} tr(W_g) \tag{3.6}$$

with $W_g = \sum_{n=1}^{N} z_{ng}(x_n - \mu_g)(x_n - \mu_g)'$.

In this respect, it is worth pointing out that Celeux and Govaert (1995) apply Monte Carlo simulations to show that this parsimonious version is capable of detecting many clustering structures even for small data sets. On the other hand, in the E-step are computed the estimated posterior probabilities as follows:

$$z_{ng} = \frac{\tau_g \Phi(x|\mu_{ng}, \Sigma_g)}{\sum_{g=1}^{G} \tau_g \Phi(x|\mu_{ng}, \Sigma_g)} \tag{3.7}$$

The EM algorithm is iterated until the relative difference between successive values of the likelihood falls below a small threshold. Finally, we assign country n to cluster g whenever the posterior probability that this country belongs to cluster g is maximum over the G existing clusters. The model-based clustering using finite mixture models approach allows us to examine whether the EU countries exhibit similar business cycle features. If these countries show business cycle features that were similar enough to consider a common business cycle pattern then only one cluster should be enough to characterize their business cycle characteristics. On the contrary, two or more clusters would indicate the existence of separate clusters with differentiated business cycle characteristics. Hence, the question of examining the similarities among the countries business cycle features may be reduced to compare two models, M_i and M_j, with i and j clusters, respectively. It is worth noting that standard likelihood ratio tests cannot be applied in this context due to the presence of nuisance parameters. Fraley and Raftery (2002) base the decision of M_i versus M_j on the model that is more likely a posteriori. Given the set of available data D, they define the Bayes factor as the ratio of the two integrated likelihoods, that is $B_{ji} = p(D|M_j)/p(D|M_i)$ and use the results of Kass and Raftery (1995) to propose that values $2ln(B_{ji})$ less than 2 correspond to weak evidence in favor of M_j, values between 2 and 6 to positive evidence, between 6 and 10 to strong evidence, and greater than 10 to very strong evidence. Finally, Roeder and Wasseman (1997) develop simulation experiments to show that, when the EM algorithm is used to find the maximum likelihood, a reliable rough equivalent to $2ln(p(D|M))$ is the Bayesian information criterion (BIC). And thus, $2ln(B_{ji})$ can be approximated through the difference between their respective BICs:

$$2ln(B_{ji}) = 2ln(p(D|M_j)) - 2ln(p(D|M_i)) \approx BIC_j - BIC_i \tag{3.8}$$

3.3. Empirical results

3.3.1. Data description

In this work, we consider a sample of countries in the same way as in the previous Chapter. It covers the European countries that belonged to the Union prior to its recent enlargements: Belgium (BG), Denmark (DK), France (FR), Germany (BD), Greece (GR), Ireland (IR), Italy (IT), Luxembourg (LX), Netherlands (NL), Portugal (PT), Spain (ES), United Kingdom (UK), Austria (OE), Finland (FN) and Sweden (SD). In addition, with the exception of Malta and Bulgaria for which the data were unavailable, we include the new members, that is, Cyprus (CY), Estonia (ET), Latvia (LA), Lithuania (LI), Poland (PO), Slovakia (SK), Slovenia (SL), the Czech Republic (CZ), Hungary (HN) and Romania (RO). Finally, we add one negotiating country, Turkey (TK), and four industrialized economies, Canada (CN), Japan (JP), Norway (NW) and the United States (US), that have been taken for comparison reasons The first best on business cycle studies consists on identifying business cycles on the basis of measures of aggregate economic activity. However, due to data availability problems, we concentrate on the analysis of the (seasonally adjusted) Industrial Production (IP) index extracted from the OECD Main Economic Indicators and the IMF international Financial Statistics Databases. As documented by Artis et al. (2005), in contrast to Gross Domestic Product (GDP) series, the IP series are available monthly, are more homogeneous across countries, and usually cover longer samples. In addition, for many economies, GDP is not based on quarterly national accounts but annual and converted to quarterly by using indicators. Finally, our time series span from 1962.01 to 2004.03. However, due to data constraints, we start the sample in 1990.01 in those exercises that include the recently acceded countries[12].

3.3.2. How similar do the business cycles look like?

Prior to analyzing the EU business cycle characteristics, we examine the potential dependence of the stationary bootstrap method to the selected block length. For robustness checking, we apply the bootstraps to expected block sizes of 19, 32 and 66 months and the results are displayed in Tables B.1 to B.3 of the Appendix B[13]. In spite of the different expected block sizes used in the computations, these tables report that the business cycle characteristics are very similar for all countries (on average, they are roughly coincident). This robustness check confirms that our results will no longer be affected by resampling with blocks of reasonable expected lengths.

Let us then concentrate on the business cycle analysis based on bootstraps with blocks of expected size of 32 months since this is the mode of the average duration of expansions in our sample of countries. For this purpose, Table 3.2 reports the median values (from 10,000 replications) of the six business cycle characteristics that have been obtained for our set of thirty countries. Some graphs can be found in the Appendix B (Figure B.1 to Figure B.3) to facilitate visual inspection. We next summarize the results.

Business cycle duration. The median duration of expansions is about 31 months meanwhile it is just about 15 months in the case of recessions. Thus, according to a broadly accepted stylized fact in the business cycle literature, expansions appear to be much longer than recessions. Of noticeable interest is the particularly strong asymmetric duration between the two phases of the cycle exhibited by Ireland, Hungary and Poland for which the percentage of time spent in expansions is roughly four times of that in recessions. On the other hand, it is worth noting that

[12]Following Blanchard (2003), we avoid atypical downturns by not using the first two years of observations of Latvia, Czech Republic, Hungary, Poland and Slovenia.

[13]We checked that mean and median values lead to similar results.

expansions have been considerably short-lived in some of the countries that have recently joined the Union as Lithuania, Latvia and Cyprus. Finally, we obtain that recessions have also been short in the set of non European countries included in the analysis as reference.

Table 3.2.: Business cycle characteristics

	Duration (months)		Amplitude		Excess	
Country	Expansions	Recessions	Expansions	Recessions	Expansions	Recessions
Austria	35.50	13	0.18	-0.06	0.15	-0.02
Belgium	28	18.75	0.12	-0.08	0.03	0.04
Germany	22.75	13.17	0.08	-0.06	0.04	-0.02
Greece	30.33	23.67	0.12	-0.09	0.31	0.08
Finland	33.33	14.25	0.22	-0.09	0.35	-0.07
France	30.67	18.50	0.08	-0.04	0.04	-0.05
Italy	18.50	16.67	0.08	-0.05	-0.01	-0.04
Luxemburg	28.33	15.50	0.17	-0.12	0.36	-0.05
Netherlands	31.33	17.67	0.10	-0.07	-0.18	-0.12
Portugal	28	22	0.14	-0.12	-0.28	-0.17
Sweden	36	15.67	0.18	-0.08	0.45	0.04
UK	36	21	0.06	-0.05	-0.01	0.07
Canada	38	11	0.15	-0.05	0.31	0.04
Norway	25	17.60	0.13	-0.09	-0.07	-0.08
Japan	29.75	16.67	0.12	-0.11	0.04	0.02
USA	34	14	0.14	-0.04	0.04	-0.03
Spain	32.25	14.25	0.12	-0.07	0.11	0
Denmark	29	15	0.17	-0.11	0.13	0.01
Ireland	47.33	10.67	0.45	-0.16	0.44	0.07
Cyprus	23.50	22	0.14	-0.16	0.22	0.17
Czech Rep.	33.67	12.50	0.17	-0.10	0.08	-0.09
Hungary	43.67	8	0.33	-0.07	1.03	0.03
Latvia	21	16.67	0.18	-0.21	-0.04	0.20
Poland	41.33	8.33	0.28	-0.06	0.35	-0.05
Slovenia	27.67	16.33	0.15	-0.11	-0.21	-0.04
Turkey	34.33	17	0.24	-0.20	0.08	-0.21
Romania	31.33	19	0.24	-0.27	-0.14	0.34
Slovakia	36.33	11	0.21	-0.09	0.18	0.05
Estonia	29	11	0.27	-0.18	-0.33	-0.15
Lithuania	20	14.50	0.23	-0.23	0.25	0.01
Average	31.20	15.51	0.18	-0.11	0.12	0

Business cycle amplitude. Again, we observe evidence of asymmetries across the phases of the cycle. Expansions are generally wider than recessions which leads the gain in terms of production in expansions (about 18%) to be considerably higher than the loss suffered from the decline of contractions (about 11%). The case of Ireland is remarkable for the extreme gains obtained during the expansive phase. Once more, Hungary, and to less extent, Poland stand out for their pronounced business cycle asymmetries. Finally, it is worth noting that eastern countries show wider and more severe recessions than other European countries.

Business cycle excess. On average, expansions are convex since the excess is positive (about 0.12). This means that expansions start with smooth growth rates of industrial production and end with steep ones. However, falls in production tend to be roughly linear during the recessive phase since the excess is about zero. In terms of the shape of the cycle, the countries with highest gains in expansions exhibit positive excess, with convex expansion periods. However, there is no a clear pattern between recession shapes and other recession features.

3.3.3. Are the business cycles more similar over time?

We conclude the section with an analysis of the evolution over time of the business cycle characteristics. For this purpose, Table 3.3 reports the business cycle characteristics for two non-overlapping subperiods: 1962.01-1989.12 and 1990.01-2004.03[14]. Comparing the two subperiods, the degree of business cycle asymmetries decreases on average. In line with the literature on the recent volatility decline (see McConnell and Perez-Quiros, 2000), cycles become smoother due to the reduction in the amplitude of both phases of the cycle. On the other hand, expansions turned into convex for most countries since the excess switches from negative to positive. This result goes in line with Kim and Murray (2002), who find that the existence of the recovery phase of rapid growth detected by Sichel (1994) is no longer present in the last expansions.

Following recent contributions in synchronization we take up now the issue of whether there is a trend to reduce the differences in the characteristics of the EMU business cycles. Since we do not have a single measure of business cycle dissimilarities as the studies of synchronization have, we ask if the distribution of business cycle characteristics across the EMU countries is becoming more similar, i.e. if the dispersion in their business cycle characteristics decreases over time. For this purpose, we compute for the two sub-samples the coefficient of variation for the duration and the amplitude, and the standard deviation for excess (the coefficient of variation is meaningless when the mean is close to zero). As Table 3.4 shows, the coefficients of variation and the standard deviations do not diminish over time. In fact, for most of the business cycle characteristics they increase in the second sub-sample suggesting that the differences in business cycle characteristics have increased rather than decreased. Inklaar and de Haan (2001) concluded that an increase in exchange rate stability have not implied convergence in the synchronization of the European

[14]Owing to data availability, we exclude the new EU members from this last analysis.

Table 3.3.: Evolution of business cycles characteristics

(a) Sample 1962.01 - 1988.12

	Duration (months)		Amplitude		Excess	
Country	Expansions	Recessions	Expansions	Recessions	Expansions	Recessions
Austria	55.20	13.75	0.26	-0.08	0.14	0.09
Belgium	44.33	12.33	0.19	-0.09	0.08	0.02
Germany	46	17.20	0.20	-0.09	-0.44	-0.12
Greece	57.80	14.33	0.36	-0.09	-0.24	-0.04
Finland	57.80	12.60	0.34	-0.15	0.01	-0.20
France	46	13.33	0.18	-0.08	0.40	0.02
Italy	49.80	14.17	0.27	-0.13	0.26	0.05
Luxemburg	28.29	16.56	0.24	-0.21	-0.20	-0.11
Netherlands	38.17	18.50	0.23	-0.10	-0.05	0.04
Portugal	56.60	12.80	0.35	-0.13	-0.14	-0.03
Sweden	40.33	21.43	0.19	-0.10	0.06	0.21
UK	41.14	14.60	0.17	-0.10	-0.24	-0.14
Canada	38.43	14	0.22	-0.08	-0.27	-0.06
Norway	50	16.50	0.32	-0.16	-0.76	0.03
Japan	58.40	12	0.41	-0.09	0.06	-0.07
USA	49.60	15.33	0.22	-0.08	-0.54	-0.14
Spain	61.75	17.50	0.33	-0.12	0.61	-0.01
Denmark	29	13.67	0.21	-0.14	-0.03	-0.16
Ireland	42.67	13.50	0.28	-0.12	0.36	-0.02
Average	46.91	14.95	0.26	-0.11	-0.05	-0.03

(b) Sample 1990.01-2004.03

	Duration (months)		Amplitude		Excess	
Country	Expansions	Recessions	Expansions	Recessions	Expansions	Recessions
Austria	35.50	13	0.18	-0.06	0.15	-0.02
Belgium	28	18.75	0.12	-0.08	0.03	0.04
Germany	22.75	13.17	0.08	-0.06	0.04	-0.02
Greece	30.33	23.67	0.12	-0.09	0.31	0.08
Finland	33.33	14.25	0.22	-0.09	0.35	-0.07
France	30.67	18.50	0.08	-0.04	0.04	-0.05
Italy	18.5	16.67	0.08	-0.05	-0.01	-0.04
Luxemburg	28.33	15.50	0.17	-0.12	0.36	-0.05
Netherlands	31.33	17.67	0.10	-0.07	-0.18	-0.12
Portugal	28	22	0.14	-0.12	-0.28	-0.17
Sweden	36	15.67	0.18	-0.08	0.45	0.04
UK	36	21	0.06	-0.05	-0.01	0.07
Canada	38	11	0.15	-0.05	0.31	0.04
Norway	25	17.60	0.13	-0.09	-0.07	-0.08
Japan	29.75	16.67	0.12	-0.11	0.04	0.02
USA	34	14	0.14	-0.04	0.04	-0.03
Spain	32.25	14.25	0.12	-0.07	0.11	0
Denmark	29	15	0.17	-0.11	0.13	0.01
Ireland	47.33	10.67	0.45	-0.16	0.44	0.07
Average	31.27	16.26	0.15	-0.08	0.12	-0.01

countries. But it seems that it has not involved convergence in the business cycle characteristics either.

Table 3.4.: Dispersion in the EMU Business cycle characteristics

	Duration (coef. of variation)		Amplitude (coef. of variation)		Excess (std. dev.)	
	Expansions	Recessions	Expansions	Recessions	Expansions	Recessions
1962.01-1989.12	0.2	0.1	0.2	-0.3	0.3	0.1
1990.01-2004.03	0.2	0.2	0.6	-0.4	0.2	0.1

3.3.4. Is there one cluster of European business cycles?

As stated in the previous subsections, there are business cycle characteristics that appear to be shared by the major European economies. However, some of them widely differ from one country to another. A telling example comes from the comparison of Ireland and the UK. While both countries exhibit similar excess in recessions (0.07), the amplitude of expansions is much higher in Ireland (45%) than in the UK (6%). In this section, we investigate the degree of heterogeneity across the EU countries' business cycle characteristics. The first question that we address is to examine whether these countries exhibit business cycle features that were similar enough to consider that there are differentiated European business cycle characteristics. On the basis of the mixture clustering approach, the analysis may be reduced to compare the likelihoods of forming just one cluster of countries with the alternative scenario of two (or more) clusters. In order to deal with this question, Table 3.5 shows the BICs and the estimated clusters for several models from M_1, which considers only one cluster, to M_5, which considers five clusters[15]. Comparing the model with one cluster with the model with two clusters, the transformation of the Bayes factor, $2ln(B_{21})$, is 6.7 that is higher than 6. This supports the conclusion that, according to the business cycle characteristics, there is strong empirical evidence against null of one European cycle.

Table 3.5.: Determination of the number of clusters

Model	BIC	2ln(Bij)
One cluster	-528.52	-
Two clusters	-521.83	6.70
Three clusters	-517.80	4.03
Four clusters	-511.72	6.07
Five clusters	-513.79	-2.07

[15]It is no worth the estimation of models with more than five clusters as there would not be enough observations to calculate all the model's parameters.

The next stage is to determine the optimal number of clusters. According to Table 3.5, the four-cluster model reaches the maximum BIC value. The difference in the BICs between the three-cluster and the four-cluster models is 6.07 which is high enough to validate that there may be four clusters of countries with cohesive and separate business cycle characteristics. These clusters and their average business cycle characteristics are reported in Table 3.6.

Table 3.6.: Average business cycles characteristics for each cluster

Clusters	Expansions			Recessions		
	Duration	Amplitude	Excess	Duration	Amplitude	Excess
Cluster 1 CY, LA, LI, ET, TK, RO	26.72	0.21	0.02	17.01	-0.20	0.06
Cluster 2 OE, LX, FN, SD, DK, US, ES, CN, CZ, SK	33.78	0.17	0.22	13.57	-0.08	-0.01
Cluster 3 BG, BD, GR, FR, IT, NL, PT, UK, NW, JP, SL	28.04	0.11	-0.03	18.10	-0.08	-0.03
Cluster 4 IR, HN, PO	44.11	0.35	0.61	9	-0.10	0.02

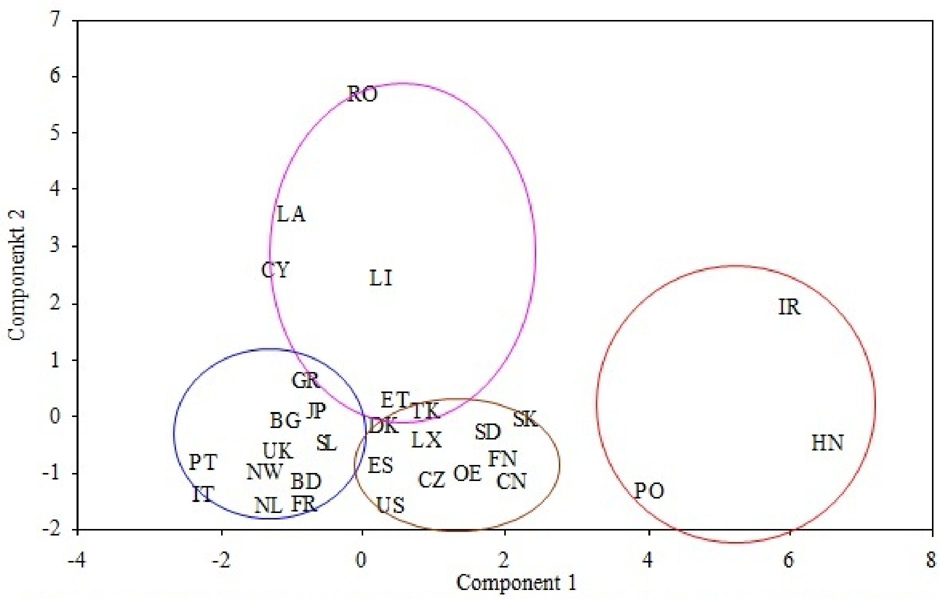
The first cluster is formed by some EU-enlargement countries, Cyprus, Estonia, Latvia, Lithuania, and Romania, and Turkey. The main characteristics of this cluster are the short duration of their expansions (with the exception of Turkey) and the high amplitude of their recessions. In particular, their expansions last just about 27 months whereas their recessions last about 17 months on average. In addition, the amplitude of their expansions and recessions is similar (about 0.20 in absolute value). Their recessions are so severe than destroy the gains of expansions.

The second cluster includes United States, Canada, some Nordic countries and two EU-enlargement countries, Slovakia and the Czech Republic. Their cycles are characterized by short and smooth recessions, and by convex expansions. In particular, they have expansions of about 34 months and recessions of about 14 months. The amplitude of their expansions is, in absolute value, twice the amplitude of their recessions. The positive excess exhibited in their last expansions reveals that growth is smooth at the beginning and abrupt at the end of the expansive phase. Hence, this cluster is characterized by long and deep expansions in relation to recessions.

The third cluster, which contains the majority of EU-15 countries, is formed by economies with low amplitude of both expansions and recessions. These countries present a mean duration of expansions and recessions of about 28 and 18 months, respectively. In absolute value, the amplitude of expansions is slightly higher than the amplitude of recessions, but in general, both are very mild.

The last cluster incorporates those countries that exhibit the most atypical business cycle characteristics: Ireland, Hungary and Poland. Their expansions are very long, wide, and convex, and their recessions very short. On average, their expansive phases last about 44 months whereas contractions last just about 9 months. In these countries, expansions exhibit an amplitude whose magnitude is more than three times the amplitude of recessions, so they are relatively very convex. Accordingly, these countries have obtained in the last years extreme positive benefits from expansions that have not been lost in recessions.

Figure 3.2.: Map of the business cycle characteristics



Notes. Acronyms used for the countries are specified in Section 3. This map is the multidimensional scaling map based on the Euclidean distance of the business cycle characteristics.

The analysis of the EMU countries and its location among clusters deserves special attention. Notice that the EMU countries are situated in different clusters and only in the first cluster there are no EMU countries. Similarly as we did in Chapter 2, we present the map of distances using multidimensional scaling. First, a simple measure of dissimilarity is calculated as the Euclidean distance in business cycle characteristics between each pair of countries. That is, letting x_{ij} denote the i-th characteristic of country j, the distance on business cycle characteristics between countries A and B is:

$$d_{A,B} = \sqrt{\sum_{i=1}^{d} (x_{i,A} - x_{i,B})^2} \tag{3.9}$$

where d is the total number of business cycle characteristics. From this exercise we obtain a set of 435 different distances. The next step is to project them in two-dimensions approximating on a plane the distances across countries in terms of their business cycle dissimilarities. In this way, countries with dissimilar business cycle characteristics are located in the map relatively far way from each other. For example, according to our previous findings, Ireland, Hungary and Poland are points far apart in the map which reflects that they exhibit the most atypical business cycle characteristics and it is exactly what is depicted in Figure 3.2. However, looking at other EU countries, it is noticeable that have more similar characteristics since they are represented by points that are closer together.

3.4. Conclusions

In this chapter, we provide a comprehensive methodology to analyze business cycle characteristics across a large set of countries with potential problems of data availability. First, we examine the minimum set of characteristics that are able to offer a complete description of the cycle. Second, we show how stationary bootstrap methods may be used to obtain the robust business cycle characteristics from time series. Our proposal minimizes typical problems of other studies on business cycles, such as the dependence of the results to the existence of mild business cycle phases, and the low number of complete cycles. Finally, we adopt from other scientific disciplines a statistical method, the model-based clustering using finite mixture models approach, to group countries with similar characteristics. We find evidence against the existence of only one European cycle whose length, depth, and shape might be representative of whole EU or the EMU area. This result reinforces the results in synchronization surveyed by De Haan et al. (2008) and points out the difficulties for the decision-making on the appropriate monetary policy stance given the differences in business cycle features. Finally, we analyze the evolution of the business cycle characteristics over the sample by breaking the sample into two sub-samples. Our results are in line with the results in synchronization obtained by Inklaar and De Haan (2001). It seems that an increase in exchange rate stability have not implied convergence in the business cycle characteristics.

4. What drives business cycle synchronization?

4.1. Introduction

In the previous chapters we have shown that some economies are more cyclically similar or closer than others. The next step is to understand what is behind those similarities and if there are macroeconomic variables that can explain the differences.

The creation of the EMU fueled a debate on the adjustment mechanism and the degree of optimality of currency unions. As we have mentioned before, the main costs of joining a monetary union are the loss of control of the monetary policy instruments and exchange rates by the national authorities. The losses are especially severe in presence of price and wage rigidities and asymmetric shocks. Under those conditions it is very difficult for the members of a monetary union to accommodate shocks. This could result in an increase in the macroeconomic divergences across economies, that could potentially undermine the monetary union. It is the famous critique that "one size does not fit all", also known as Walter's critique.

What is the probability that asymmetric shocks or symmetric shocks with asymmetric effects happen in a monetary union? Many works have tried to answer this question theoretically and/or empirically, but the issue is not solved yet. Most of them agree in that the closer is the area to be an optimal currency area, the less likely is the occurrence of these events. The theory of Optimal Currency Area (OCAs) developed by Mundell (1961) pointed to several criteria[1]. Basically the idea of these criteria is that the more similar or homogeneous are the economies which decide to get integrated and form a monetary union, the more likely it is that they are an OCA. Is the EMU an OCA? There are some works that raised doubts about it due to the substantial and persistent heterogeneity across Euro area countries. In any case, these criteria are endogenous as Frankel and Rose (1998) argued. Therefore, it is possible that in the very beginning the members of a union do not fulfill these criteria, but over time they can manage to do it. For instance, the adoption of a common currency has reduced transport costs and boosted trade flows among Euro

[1]As mentioned before in the introduction, the Optimal Currency Area (OCA) criteria are: i) labor mobility (Mundell, 1961); ii) diversification of the production (Kennen, 1969);iii) trade openness (McKinnon, 1963); iv) existence of fiscal transfers; v) homogeneity of tastes and preferences; vi) to share the vision of a common destiny.

area countries. At the same time, the reduction of volatility in the exchange rates has also promoted trade with countries outside the area. Thus, the Euro would have enhanced trade openness, one of the OCA criteria.

Among these endogenous criteria, it is crucial what happens with the diversification of production (Kennen's criterion). On the one hand, Krugman's specialization paradigm predicts that as countries become more integrated, they also become more specialized. The lower transport costs are going to increase trade flows, and this is going to make specialization in production more attractive to take advantage of economies of scale and agglomeration effects. However, this will also increase the probability that asymmetric or idiosyncratic shocks happen, leading to more asymmetric and non-synchronous fluctuations in the EMU.

There are more optimistic views in which the monetary and financial integration would endogenously provide a mechanism to absorb idiosyncratic shocks, even if the countries were totally specialized. The monetary union may also intensify the intra-industrial trade and make it less necessary for the countries to specialize. In this way the production will be more diversified with more homogeneous production structures across countries and the business cycles will tend to converge.

The purpose of this chapter is to study the main determinants of the cyclical synchronization across countries and at a regional level. Regarding the first case, we consider all members of the EU-27 and several other developed countries. We find two main determinants that have been discussed in the literature: the trade intensity and the degree of financial integration. This means that the removal of barriers to the mobility of goods, services and capital could facilitate the transmission of shocks across countries. The structure of the chapter is as follows. In Section 2 we review the literature on business cycles and their determinants. Section 3 presents the empirical results and Section 4 concludes.

4.2. Literature review

Although economic theory predicts that the positive effects of economic integration dominate the synchronization of business cycles, the empirical studies, especially for the Euro area, have found different results. Most of them agree in that the cyclical synchronization in this area has increased, notably since 1992 and 1993, when the European Monetary System (EMS) was abandoned. In fact, the integration process which began from that point in time on contributed to intensify this comovement as demonstrated by Azevedo (2002), Koopman and Azevedo (2003) and Crespo-Cuaresma and Fernández-Amador (2010). On the other hand, there are works with no such positive results of the economic integration for the business cycle comovements. For instance, Harding and Pagan (2006) found a relatively low correlation among the cycles in the EMU countries, and Croux et al. (2001) showed that the business cycles across the states in the US are more similar than the cycles in the EMU countries. However, Inklaar and De Haan (2001), Wynne and Koo (2000), Agresti and Mojon (2001) and Beine et al. (2003) concluded that the cycles of the EMU founder countries are more synchronized among themselves than with those countries which joined the EU in the last rounds and also with the periphery countries. Sopraseuth (2003) and Garnier (2003) found that the correlation of the German business cycles is higher with its European partners than with the US although there is no evidence of an increase in the cyclical synchronization. For Hallet and Richter (2004, 2006), this correlation has decreased over time, and it is particularly unstable between the United Kingdom and the Euro area countries. In agreement with this result, Massmann and Mitchell (2004) show that in the last forty years periods of cyclical convergence have alternated with periods of cyclical divergence in the Euro area. In the most recent period they find some evidence for increasing synchronization. To sum up, there is no consensus in the literature regarding the effects of the economic integration of the Euro area on the business cycle comovements.

Studies at a regional level reveal a similar picture. For instance, Fatas (1997) and Belke and Heine (2004) show that the cyclical comovement across the EU regions has decreased in the nineties. In contrast, Montoya and de Haan (2008) provided evidence in favor of an increase in the regional cyclical synchronization in the EU-15 from 1975 until 2005, except for part of the eighties and the beginning of the nineties. And Clark and van Wincoop (2001) found more synchronicity across European regions for most of the EU-15 countries and the states in the US than across EU-15 countries.

Given this lack of agreement, some works focus on understanding the cyclical comovement by looking at the factors that determine it. The seminal paper in this literature is Frankel and Rose (1998), which found a strong and positive effect of trade in explaining the correlations across economies. However, although there is more or less a consensus regarding the importance and the sign of the effect, there are discrepancies in relation to its magnitude. For instance, Kose and Yi (2002) estimated a greater impact than Frankel and Rose, whereas it was much smaller in Gruben et al. (2002) and Inklaar et al. (2008). Bordo and Helbling (2004) got mixed results but agreed that trade linkages are relevant in explaining comovements. Ng (2007) distinguished between vertical specialization and intra-industrial trade. The former has a positive effect on synchronization and the latter, in agreement with Garnier (2004), is close to zero. In this way, controlling for these two effects, the total trade has a negative impact in cyclical correlation.

Apart from the trade intensity, there are other variables that have been considered in the literature and are equally important. Imbs (2004, 2006) and Schiavo (2008) found that capital market (i.e. financial) integration is positively related to the cyclical comovement. Furthermore, this variable has direct and indirect effects because it also affects the level of productive specialization as well as the volume of international trade. Otto et al. (2001) includes foreign direct investment, the spreads or interest rates differentials, the volatility of exchange rates and interest rates, and differences in the industrial structure. An interesting aspect of this work is that when it includes variables such as sound accounting practices, development of new technologies and common legal system, they are significant. However, in this case the trade intensity and the industrial structure become statistically insignificant. Furthermore, Kose et al. (2003) accounted for an index of restrictions in the capital account and the volatility in the interchange relationship, and in this way trade openness turned out to be not statistically significant. On the other hand, Calderon et al. (2007) consider a larger sample of countries, and although the effect of trade was positive and significant, it was smaller for the developed countries. They concluded that the bigger the divergence in the productive structure, the lower is the impact of the trade relations on the cyclical correlation.

Several works have included variables of fiscal and monetary policies. Clark and Van Wincoop (2001) analyze correlations across regions in the US and Europe, and find an important role for fiscal variables. Darvas et al. (2005) show that the difference in the budget positions (cyclically adjusted) across countries affects the correlation. Inklaar et al. (2008) consider that the similarities in fiscal and monetary policies together with the similarity in the composition of the trade flows and the existence of a common currency have an important effect on the cyclical synchronization, comparable to the trade intensity effect.

Regarding the volatility of the exchange rates, it has no clear effect on the synchronization. Although Bergman (2004) and De Haan et al. (2002) estimate a positive impact of this variable, Bordo and Helbling (2003) do not find robustness in these results.

At a regional level, De Grauwe and Vanhaverbeke (1993) show how the flexibility of the exchange rates plays a crucial role in the adjustment to shocks across regions, given that asymmetric shocks happen more frequently at this level. Montoya and de Haan (2008) and Clark and van Wincoop (1999) stress the role of the borders, with stronger effects in Europe than in the US. This has to do with the lower volume of trade and the high specialization of the European regions in relation to the American federal states. Taking all this into account, Clark and van Wincoop predicted that it is not likely that the common currency fosters cyclical synchronization. Pons-Novell and Tirado-Fabregat (2006) also point to the importance of the geographical location in the symmetry of the regional business cycles in Europe. For the case of the Spanish regions Gadea et al. (2011) also find that neighborhood matters, and interestingly, a relationship between the disparities in labor market performance and human capital and the regional business cycle synchronization.

In Barrios and Lucio (2003) the relative size and the industrial structure are the key determinants of the regional cyclical synchronization. Furthermore, they think that the integration process has had a positive influence, and it is likely that there arise networks or groups of cyclical convergence in Europe. However, many works have continued exploiting the heterogeneity of the productive specialization as main explanatory variable. For instance, Kalemli-Özcan, Sorensen and Yosha (2001) pay special attention to the degree of regional specialization as key determinant of the cyclical divergences at a regional level and find that the regions more specialized in production exhibit less symmetric fluctuations. Given this result, this work predicts that the economic integration will lead to a better income insurance through greater capital market integration which will, ceteris paribus, induce higher regional specialization in production, and therefore, a dominant role of the asymmetric shocks. The more a country can gain from sharing idiosyncratic risk with other countries in a group, the more asymmetric are its shocks relative to the group. And for Belke and Heine (2006), the increasing specialization at a regional level (agglomeration effects) explains the decrease of synchronization of regional business cycles. However this effect is insignificant at the national level because the industrial structures tend to be similar across countries.

4.3. Empirical results

4.3.1. Data

The measure of cyclical divergence in this work are the pairwise distances (based on the comprehensive measure of correlation) that we proposed in Chapter 2. In this way, the lower the distance, the more similar are the cycles. The literature typically has considered two fundamental explanatory variables: the trade intensity and the degree of financial integration. Frankel and Rose (1998) proposed three measures of bilateral trade intensity; one based only on exports, another based on imports, and a third one combining both. The latter is defined in terms of the summation of nominal exports X_{ijt} and imports M_{ijt} from country i to country j, divided by the total amount of exports and imports of country i , $X_{i\bullet t} + M_{i\bullet t}$, plus country j, $X_{j\bullet t} + M_{j\bullet t}$.

$$TI_{ijt}^{FR} = \frac{(X_{ijt} + M_{ijt})}{(X_{i\bullet t} + X_{j\bullet t} + M_{i\bullet t} + M_{j\bullet t})} \tag{4.1}$$

In this respect, our measure is different from the standard measures of trade linkages in the literature. Assume that a country i can export or import its cycle to another country j if the proportion of imports or exports coming from or going to the other country is high. In order to account for those relations, we create the trade variable as the maximum of two different averages (over the sample): the proportion of exports of country i that go to country j and the proportion of exports of country j to country i[2]. For example, in the case of Austria and Germany, the average proportion of Austrian exports going to Germany is 37%. The average proportion

[2] We tried the same measure with imports with almost identical results. Actually, the correlation between both measures is 0.93.

of German exports going to Austria is 5%. Therefore, for this pair of countries we will use 37% as the trade linkages across them. The idea behind using the maximum is that if business cycles are linked to trade and a small economy has strong trade linkages with a big economy, we will observe that the business cycle of the small economy is linked to the business cycle of the big one. We can express our measure as:

$$TI_{ijt} = max(\frac{X_{ijt}}{X_{i\bullet t}}, \frac{X_{jit}}{X_{j\bullet t}}) \tag{4.2}$$

The trade variable is fundamental in explaining the relations across economies. However, the trade variable presents a serious problem of endogeneity[3]. We solve this problem by estimating the equation with instrumental variables. We use the standard instruments in the literature for explaining trade: a border dummy, the log of geographical distances, a Euro dummy, a European Union dummy, and the absolute difference in the log population[4]. However, it is true that these instruments can also be problematic, because it is possible that some of the other explanatory variables are correlated with them. For instance, neighbor countries are more likely to coordinate their policies. One solution is not to include additional explanatory variables. But in such a case the regression coefficient of trade would be biased due to the omission of relevant variables.

Furthermore, higher trade openness usually means higher inter-industrial and intra-industrial trade. The intra-industrial trade can also boost specialization in production with a negative impact on cyclical comovements.

The process of economic integration can enhance not only trade but also financial integration. An increase in financial integration implies a better income insurance because it provides a mechanism to absorb idiosyncratic shocks or reduce the impact of asymmetric shocks, leading to more symmetric fluctuations. On the other hand, the insurance could endogenously promote specialization in production and, therefore, less symmetric cycles. It is not easy to find or define an indicator of financial integration. We tried several indicators like the private credit or the market capitalization with unsatisfactory results.

However, the specialization in production in our model is captured by two variables, the pairwise differences (in absolute value) of the percentage of industry production

[3] It might be a problem for some other variables used in the estimation, particularly the policy ones. However, we think that the problem is partially solved by taking averages at the beginning of the sample as explanatory variables for future comovements. This caveat do not apply so clearly to trade because trade structures and trade relations are deeply related with business cycle comovements.

[4] The dummies take on the value 1 when both countries share a common border or both belong to the Euro area or EU, respectively. A Sargan test for the correct specification of the orthogonality restrictions clearly does not reject the null of correct specification (p-value 0.33).

in total production, and the percentage of agriculture in total production. We found them to be more informative than the popular Krugman (1993) index of specialization that aggregates the pairwise differences in the production of all sectors.

In relation to the macroeconomic policies, there is an agreement in that the more similar they are, the more symmetric will be the fluctuations. With respect to monetary policy, the monetary integration involves a higher stability in exchange rates but also a common monetary policy. In principle both have positive effects on the cyclical synchronization. On the other hand, the exchange rates can be a mechanism to absorb shocks. If asymmetric shocks hit the monetary union, the common currency could imply that all the adjustment relies on the real economy, leading to more cyclical divergences among the members of the union. We tried lots of possible combinations to include monetary policy variables (inflation differentials, inflation correlations, etc), but they led to no improvement.

It is also important to consider the influence of fiscal policy. Our indicator is defined as the difference (in absolute value) in the public balance (net borrowing or lending) as percentage of the GDP. Countries with high public imbalances in relation to the others will have more difficulties to deal with asymmetric shocks and, therefore, their cyclical movements will be less symmetric.

Finally, we include two additional variables to take the structural differences into account. On the supply side, we consider the labor productivity or output per employee as the main determinant of economic growth in the long-run. This picks up the differences in the technology of production across countries. On the demand side, we include the savings ratio which is related to consumers' spending and captures differences in consumers' preferences. However, as this variable is also related to investment, it might also reflect the differences in the economic policies and the financial integration.

All the variables represent differences from country i to j. In contrast to other studies that take one country or the whole sample of countries as reference, the analysis is made by pairs of countries. In all cases, the macroeconomic variables used as explanatory variables are sample means for the longer period of information available. We intend to capture the structure of the economy and avoid as much as possible all the cyclical variation in the variables. More information about the data sources can be found in Table C.1 of Appendix C.

4.3.2. Results

In this section we always refer to the comprehensive measure of cyclical distance as dependent variable. The main results for our preferred specification are displayed in Table 4.1. In the Tables C.2 and C.3 of Appendix C we show some statistical descriptives for the dependent and explanatory variables, and the regressions using the other three measures computed in Chapter 2 with almost identical results.

The results in Table 4.1 show that trade is a very important variable in explaining the business cycle comovements and with the expected negative sign. This means that when the trade intensity between two countries is high, their cyclical distance is predicted to be low (i.e. they are highly synchronized). Pairs of countries with a high level of this variable are closer together, which implies that there is a transmission of the cycle through trade. Therefore, countries that are more linked by trade are also more linked in their business cycles. The discrepancies in industrial and agricultural production are highly significant. Therefore, we can conclude that the specialization of the economy has also an important role in the business cycles synchronization across countries. Other significant variables are differences in the average saving ratio and the average labor productivity. Notice that although significant and positive the impact of differences in productivity is not very big. However according to this result, the heterogeneous behavior of the labor productivity across countries (Jimeno et al. 2006) and regions (Cuadrado-Roura et al. 2000) in Europe contributes to reduce the level of cyclical comovement. Finally, it is important to remark the role of the policy variables. The fiscal variables are significant but monetary policy related variables do not seem to explain the cyclical differences.

Table 4.1.: Business cycles distances and macroeconomic variables

Dependent variable: Distances based on the comprehensive measure

	OLS	IV
Constant	0.58 (0.02)	0.58 (0.03)
% Industry	0.84 (0.18)	0.83 (0.19)
% Agriculture	1.55 (0.26)	1.54 (0.26)
Saving ratio	0.36 (0.17)	0.36 (0.17)
Lab. productivity	0.08 (0.04)	0.08 (0.04)
Public balance	0.56 (0.23)	0.55 (0.24)
Trade	-0.86 (0.14)	-0.64 (0.27)
R-squared	0.30	
Sample size	435	

Note: Values in parentheses are the standard deviations.

4.4. Conclusions

In this chapter we find a role for different macroeconomic variables in explaining the comovements across economies. We consider that our results are fundamentally different from the previous results found in the literature where most of the variables except trade were not significant. In contrast to the standard results in the literature, we find that, apart from trade, there is a significant role for other structural and economic policy variables to explain business cycle comovements. What we can conclude from all this is that the smooth transition towards a more integrated economic area could be due to the existence of previous strong business cycles correlations and linkages, fundamentally through trade.

5. Changing correlations, macroeconomic risk and the business cycle

5.1. Introduction

The recession that started by the end of 2007 in the United States and later on in Europe, popularly known as the *great recession*, has put a question mark on some traditional methods for forecasting. The majority of these models were incapable of predicting the timing and also the magnitude of the recession. With the high uncertainty about the recovery and indicators that were sometimes misleading, forecasting has become more challenging. As a matter of fact, the magnitude of the recession was so important that it is comparable to the recessions of the 1970s and so unusually big for the recent times that it has become very complicated to make predictions about the future with traditional methods. Some people have included financial variables in their macro models to account for the volatility, because the recession started as a financial crisis and the financial sector has a more important role than ever. However, there is increasingly a consensus that what is crucial is to take into account the changes in the level of uncertainty or volatility in models to predict macro variables such as GDP or inflation. In other words, macroeconomics and volatility are closely related because finance and macroeconomics are more interconnected than ever.

After the double-dip recession in the USA in the beginning of the 1980s, there was a process of declining variance of the main macroeconomic aggregates called the *great moderation*. Since then, the cycles were smoother, especially the recessions, but also the recoveries were milder. As stated in Chapter 3, the same smoothing phenomenon was observed in Europe, although not as markedly. However, the last recession involved a sharp decline in output growth. In the specific case of the Euro area, where the available historical data set is not as long as for the US, the small sample size aggravates the problem because the impact of the most recent observations is inversely proportional to the length of the data that precede it. All the models, and in particular the Dynamic Factor models (DFM), failed to predict the great recession. The key question is why they were not able to do it.

There is a consensus in the economic literature about some stylized facts for key macroeconomic time series. First, there is a strong *comovement* or *correlation* among most of the macroeconomic indicators, especially at business cycles frequencies (from the earliest works by Burns and Mitchell (1947), Geweke (1977) and Sargent and Sims (1977), to the most recent ones which exploit this comovement by means of factor models to predict GDP growth, among others Camacho and Pérez-Quirós (2010) or Angelini et al. (2011)). This explains the popularity of factor models to estimate and forecast the business cycle. Second, in crises episodes the volatility of most indicators increases (see Engle (1982) and Stock and Watson (2007) for inflation; Weiss (1984) and Ewing and Thompson (2008) for industrial production; Ho and Tsui (2003) and Fang, Miller and Lee (2008) for GDP growth). This is what is called *volatility clustering* or non-constancy of the conditional variance over time. Third, the aforementioned phenomenon occurs simultaneously in many macroeconomic series. Therefore, we can conclude that there exists *volatility comovement* (related works: Bollerslev (1990) for exchange rates; Cappielo, Engle and Sheppard (2003) for equities and bonds; Ho, Tsui and Zhang (2009) for sectoral industrial production). And finally, given that the volatility is higher during recessions than expansions, there is a *leverage* or *asymmetric effect* because negative shocks have a higher impact on volatility than positive shocks (see for instance Ho and Tsui (2003) and Fang , Miller and Lee (2008) for GDP growth, Ewing and Thompson (2008) for industrial production, and Ho, Tsui and Zhang (2009) for sectoral industrial production). Many models, such as the popular DFMs, have focused on the first stylized fact without considering the others. But the recent crisis has shown how important it is to take them into account.

In his recent book "Anticipated correlations" (2009) Robert Engle indeed pointed out that a model which does not update volatilities and correlations will make much bigger mistakes when the markets are changing. The literature on business cycles has focused on the comovement and the non-linear behavior of the conditional mean in order to identify recessions and expansions, without explicitly considering time-varying features of higher order moments (e.g. conditional variances or correlations). However, conditional heteroscedasticity, asymmetric volatility and time-varying conditional correlations have important implications for business cycle theory and especially for forecasting. Furthermore, Nelson and Foster (1994) argued that phenomena like fat residuals or leverage effects are potentially more important than misspecifying conditional means. For all these reasons we think that the comovement story is incomplete when the dynamics of the second order moments are not considered.

The aim of this chapter is to study in which ways we can modify the standard DFMs to take into account the non-constancy of second conditional moments (i.e. the variance and the correlations). Our point is to take this instability into account in the most parsimonious way by introducing time-varying variances in the common factor of the DFM. As we will discuss later, this involves that the conditional correlations are also time varying. We will show that DFMs under serial heteroscedasticity do a better job at forecasting than under homoscedasticity. Our empirical strategy entails several advantages: i) we get an estimate of the volatility as a by-product;

ii) we take into account the changing level of uncertainty in the confidence intervals for the conditional mean forecasts; and iii) the implicit conditional correlations are time-varying. However, this comes at the cost of introducing an additional source of error, because in some cases the parameters of the volatility models are difficult to estimate.

The structure of the chapter is as follows. Section 2 reviews the literature on how works in macroeconomics have dealt with the volatility problem. In Section 3, the DFMs and possible extensions to account for time-varying variances are presented. The results of a Monte Carlo experiment are explained in Section 4, and Section 5 presents Stock and Watson's (1991) coincident indicator as empirical application. Section 6 concludes.

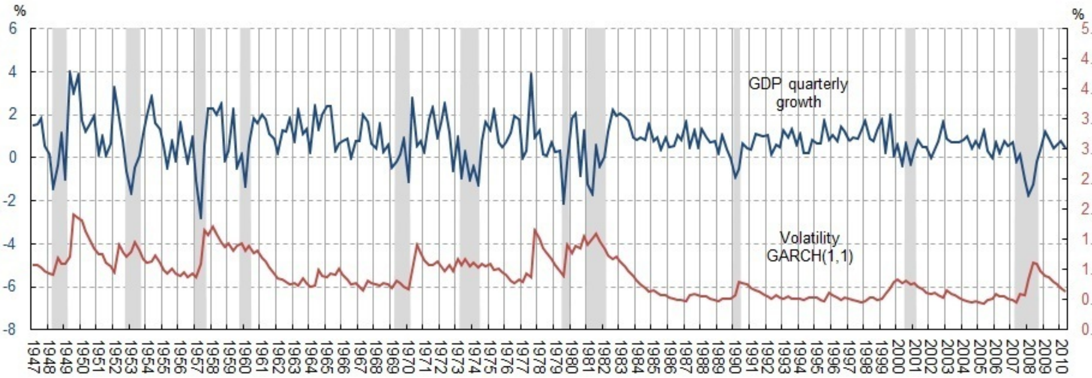
5.2. Macroeconomics and volatility

5.2.1. Some stylized facts

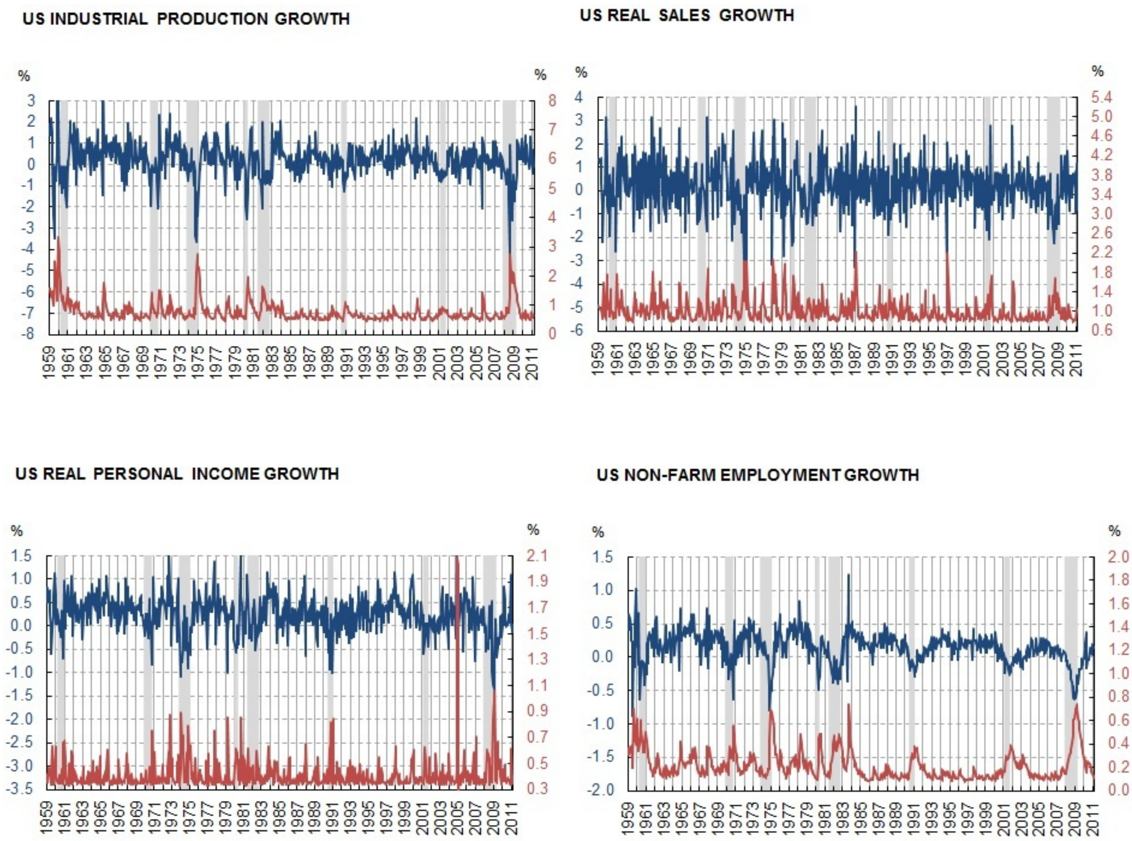
The data we are going to use in this work correspond to the four monthly indicators that Stock and Watson (1991) used to construct a coincident indicator for the United States and that the National Bureau of Economic Research (NBER) closely monitors to date peaks and troughs in the economic activity. These indicators are: i) The industrial production index which is a monthly measure of production. The main shortcoming is that it only represents manufacturing, mining and utilities sectors, excluding services and government sectors. ii) The real personal income less transfers, which is the monthly measure closest to real Gross Domestic Product (GDP) precisely due to the fact that the transfers are subtracted and the nominal series is deflated with the interpolated quarterly GDP implicit price deflator. iii) The employment series which is typically monitored and included in Stock and Watson's indicator is the number of non-farm payroll employees. It consists of the number of filled jobs in the business sector excluding agriculture and is based on the Current Employment Survey (CES). iv) Finally, the real manufacturing and trade sales is another monthly indicator of output, although it only includes sales of goods and imported goods but not services. In order to be comparable to real GDP, the nominal sales are deflated in the same way than the personal income.

Figure 5.1 represents the rates of growth and the estimated volatilities using simple GARCH(1,1) models for the quarterly real GDP and the four monthly variables of Stock and Watson's (1991) coincident indicator for the US mentioned above: industrial production, real personal income less transfer payments, real manufacturing and trade sales, and non-farm payroll employment. We see that the majority of these indicators exhibit a higher conditional variance during recessions, especially in the recessions of the 1970s and the last one in 2007. We also observe a global reduction in total variance since the mid-1980s (i.e. the great moderation).

Figure 5.1.: Volatility of some macroeconomic variables in the US



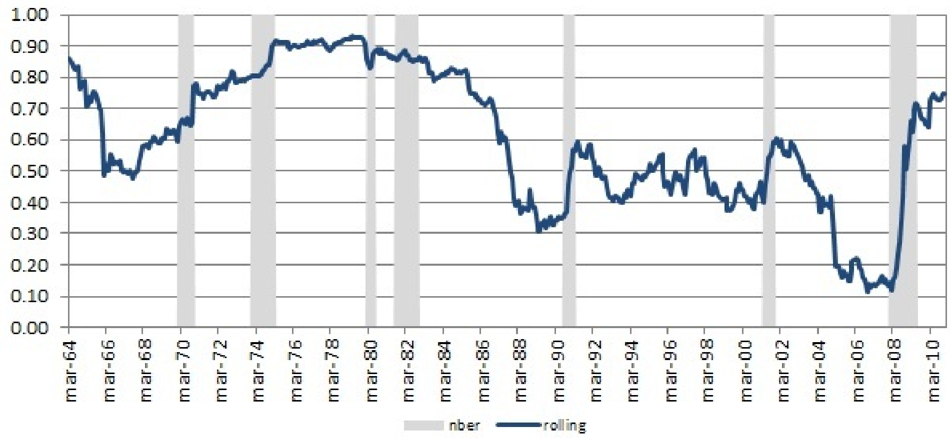
(a) Real GDP



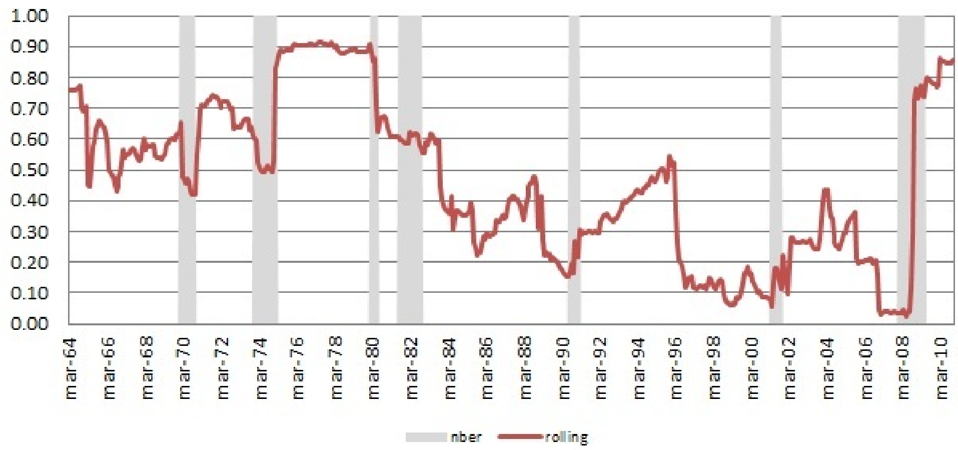
(b) Several monthly indicators

In the top of Figure 5.2 we plot the absolute value of the determinant of the correlation matrix as a measure of linear relationship for these series. It will be 0 if the variables are perfectly and positively correlated, and 1 whenever the variables are not correlated at all. In order to make this measure more intuitive, we represent it as 1 minus this determinant. In this way, values close to 1 indicate highly correlated series and 0 the opposite. It is computed using a rolling window of 5 years over the sample from 1959 to 2011. We observe that the total mass of correlation in general has decreased over time as it had passed from values around 0.8 to around 0.3. There is a turning point around the mid-1980s, at the time of the great moderation, but during recessions (shaded areas are the officially dated recessions by the NBER) the correlations increase, especially during the great recession.

Figure 5.2.: Measures of comovement and volatility comovement



(a) Comovement



(b) Volatility comovement

In the bottom of Figure 5.2 we show the same measure of global comovement as before but this time for the estimated volatilities. The graph shows that there exists a certain comovement between the volatilities, in particular during recessions. What we can conclude from all this is that the instability and asymmetries in variance are transmitted to the correlations in a way that times of common high volatility coincide with times of high correlation. Therefore, the correlations are also time-varying.

5.2.2. The importance of variance

As Hamilton (2008) stated, most macroeconomic studies have concentrated their efforts on the conditional mean disregarding the information contained in the conditional variance. However, there is an increasing number of more recent works that stress the importance of accounting for variance instability for the reliability of the results.

The most well-known problem caused by non-constancy of the variance is the *inefficiency* of the estimates. The estimation of linear models by Maximum Likelihood (ML henceforth) is consistent even when GARCH effects in the disturbance are ignored (Weiss, 1984), but the estimators will not be efficient any more. Hamilton (2008) shows that, even when our main interest is the conditional mean, modeling the conditional variance correctly is important for two reasons: i) OLS standard errors can be misleading and result in spurious regressions because we strongly reject a true null hypothesis (i.e. type I error); ii) the inference about the conditional mean can be badly influenced by outliers and high-variance episodes.

Another issue are *identification problems*. Fiorentini and Sentana (2001) found that if factor models are estimated without taking time variation in the conditional variances into account, neither the loading matrix nor the noise variance are identified without extra restrictions. However, the identification problems are somehow alleviated when this variation is accounted for, as there is a relative efficiency gain which increases with the variability of conditional variances.

In estimation methods like ML there could be *convergence problems* due to a complicated shape of the likelihood with multiple modes and some flatter regions. This could even result in Heywood cases, a case in which ML accommodates the parameters to reach maximum in-sample fit, with absurd parameter values such as negative or zero variances. The likelihood can also have a point mass at zero values of the parameters (Stock and Watson, 1998), which is known as pile-up problem. Usually this occurs when there are convergence problems because the algorithm is going through points in a region of non-identification. On the other hand, as pointed out by Box-Steffensmeier and Lebo (2008), in methods like rolling window estimation or the popular Kalman filter, the most volatile period dominates the estimations making the model lose memory. In the rolling window case it is because the rolling estimation introduces a small sample bias. In the Kalman filter estimation, as we will see later, it is due to the construction of the filter.

5.2.3. Literature review

There is an agreement in the literature that mean shifts are less important for the variance than variance shifts are for the mean. In this respect, some works in the literature of structural break tests in mean have noticed that the distribution of the test statistic may be affected. Two of the proposed solutions are to consider either bootstrap p-values adapted to the instability of variance for these tests (e.g. Blocks or Wild bootstrap) or Bayesian mixture innovation models (Gerlach et al. (2000) and Giordani and Kohn (2008)).

Regarding the literature based on unobserved component (UC) models, Bos and Koopman (2010) notice the relevance of modeling the mean and the variance at the same time in an univariate UC model for industrial production. They introduce stochastic volatility to improve the fit of the model because in this way observations from non-volatile periods receive more weight.

In the VAR and SVAR literature the most influential works which have introduced time-varying variance in this framework are those trying to explain the reasons for the great moderation in the US. Basically there are two theories: good policy vs good luck. The good policy approach argues that changes in the transmission mechanism of monetary policy played a role in the great moderation. In contrast, the good luck story focuses on the reduction of the volatility of the shocks. From a practical point of view, for disentangling both effects it is necessary to extend the VAR/SVAR models in a way that the variance of the shocks is time-varying and the impulse responses or covariances also change over time, as in Primiceri (2005) and Koop et al. (2009).

In relation to the identification of turning points, Chauvet and Potter (2010) demonstrated with Bayesian probits that the best model to predict turning points in the economic activity for the US is one with recurrent breaks in variance, and Creal, Koopman and Zivot (2010) show that the beginning of the recession in 2007 is better identified when they introduce stochastic volatility in their multivariate trend-cycle decomposition model.

For forecasting, most of the works that combine mean and variance modeling at the same time are at an univariate level. Espasa et al. (2010) at a univariate level and Alessi et al. (2009) at a multivariate level show that identifying the source of uncertainty helps.

When we turn to DFMs, there are very few works that have extended these models to account for changes in variance. There are different ways in which the variance could adapt over time. On the one hand, it could be observation-driven, such as in GARCH models, where the conditional variance depends on past observations. Alternatively, it could be parameter-driven, such as in Stochastic Volatility (SV) models, because the conditional variance depends on a latent (or unobserved) component estimated in a state space model. The latter is more flexible although more complicated to estimate. It is important to notice that these time-varying parameter (TVP) models work well when the changes in the parameters are gradual ("many small breaks"). Large and infrequent breaks, such as the great moderation, are more difficult to pick up with these models, especially with the observation-driven approach.

There are two influential papers based on the observation-driven approach. First, Harvey, Ruiz and Sentana's (1992) static factor model including ARCH for the variance of common and idiosyncratic factors. They show the importance of including a correction term in the estimation that accounts for the estimation error in the unobserved factor. Second, Alessi, Barigozzi and Capasso (2009) estimated a dynamic factor model distinguishing between static and dynamic factors. The static factors are linear combinations of dynamic factors and are orthogonal. In contrast, the dynamic factors (or common shocks) are correlated. This fact allows to exploit the multivariate dimension to account for time-varying variances in the model as the variance-covariance matrix of the dynamic factors will follow a multivariate GARCH model[1]. Therefore, the static factors will be weak GARCH processes. The variance of the idiosyncratic factors will follow independent and univariate GARCH models. In the empirical example, they demonstrated that this approach leads to a small improvement in forecasting inflation at different horizons. As a by-product they get estimates and forecast of the conditional volatility and the covariances. Their model can be considered a special case of the structural ARCH developed by Harvey et al. (1992). But notice that this paper belongs to a growing literature on multivariate volatility models which are related to the conditional heteroscedastic DFM. The philosophy of multivariate volatility models[2] is slightly different from the traditional DFM as their purpose is to estimate and explain conditional variance-covariance matrices with the observed variables. But Sentana (1998) demonstrated that under certain conditions, they are observationally equivalent.

Regarding the parameter-driven approach, a recent paper by del Negro and Otrok (2008) estimates from a fully Bayesian perspective a DFM in which all parameters are time varying. The variances follow geometric random walks and the loading coefficients are random walks. In this framework many strong assumptions are required in order to identify the model. In contrast, Stock and Watson (2010) proposed a DFM with stochastic volatility in the variance of common and idiosyncratic factors. They account for the large break in variance of the great moderation by introducing dummy variables. In the next section we will provide more insights about how to extend traditional DFM to account for variance instability.

[1] They consider two possibilities: a BEKK model and a Dynamic Conditional Correlation (DCC) model.

[2] See a survey on multivariate GARCH models in Bauwens, Laurent and Rombouts (2006).

5.3. Dynamic Factor models and volatility

5.3.1. Dynamic Factor models

Traditional factor models (e.g. the static factor model, the generalized dynamic factor model, etc.) have been successfully employed to forecast the conditional mean of macroeconomic variables such as inflation or GDP growth. Typically, they assume that there are some common unobserved factors that help to explain the comovement of the series, although this does not explain the whole behavior of the series. There is a part that is specific to each series which is the idiosyncratic component. In order to identify these components some assumptions are required. Here we present the state-space representation of a simple factor model:

$$y_t = Hf_t + \xi_t, \tag{5.1}$$

$$f_t = Ff_{t-1} + u_t \tag{5.2}$$

with $\xi_t \backsim N(0, R)$ and $u_t \backsim N(0, Q)$, where $y_t = \{y_{1t}, ..., y_{Nt}\}$ is the vector of N series for $t = 1, ..., T$; $f_t = \{f_{1t}, .., f_{kt}\}$ is the vector of K common factors that follow an autoregressive model (for simplification we assume $p = 1$); and $\xi_t = \{\xi_{1t}, ..., \xi_{Nt}\}$ is the vector of N idiosyncratic components. To simplify we do not introduce dynamics in this component. H is a NxK matrix with the factor loadings in the measurement Equation 5.1, F is a KxK matrix of the autoregressive coefficients for the transition Equation 5.2, and R and Q are the variance-covariance matrices of the idiosyncratic components and the innovations in the factor equation. Both are diagonal matrices of dimensions NxN and KxK, respectively.

To identify the unobserved components the following assumptions are usually made: i) u_t is an orthonormal white noise involving that $var(u_t) = Q = I$. This normalization assumption is crucial to identify the loadings and factors; ii) ξ_{it} is a zero-mean stationary process and independent across i; iii) ξ_{it-k} and u_{jt} are mutually orthogonal (independent), for all integer k, i, and j (i.e. exact factor model). This orthogonality assumption is sometimes relaxed to allow for a limited amount of cross-sectional correlation (i.e. approximate factor model). Assumptions ii) and iii) guarantee that all the comovement comes from the common factors and make it possible to identify common and idiosyncratic factors. Notice that this model implies the variance-covariance decomposition

$$var(y_t) = \Sigma = Hvar(f_t)H' + R \tag{5.3}$$

Regarding the estimation method, Maximum Likelihood with Kalman filter[3] is typically the preferred method for small or moderate N, and Static and Dynamic Principal Components Analysis (PCA and DPCA) for large N. Fiorentini and Sentana (2001) showed that by estimating these models without taking time variation in the conditional variances into account, neither the loading matrix nor the noise variance were identified without extra restrictions. However, if only some factors have conditional heteroscedastic variances and we take it into account in the estimation, the loading matrix is identifiable. Therefore, the identification problems are alleviated when variation in factor variances is accounted for because there is a relative efficiency gain to estimate the loading matrix and the variances of the idiosyncratic components, which increases with the variability of the conditional variances. Besides, the indeterminacy of factors is small when the variance of idiosyncratic components is small compared to the variance of the common component, $Hvar(f_t)H'$. This means that in the hypothetical case that $Q = I$ and $F = I$, if the trace of $HR^{-1}H'$ is large, the indeterminacy of the factor is small. Notice that in this case the inverse of the idiosyncratic variance-covariance matrix R^{-1} is also the inverse of the signal-to-noise ratio, and H will be unique if $HR^{-1}H'$ is diagonal.

An efficient method to estimate the state variables given the parameters is the Kalman filter. This filter estimates the state variables as a weighted average of the most recent observed values of the variables together with the past values, $f_{t+1|t} = \sum_{j=1}^{t} w_j(f_{t+1|t})y_j$. Koopman and Harvey (2003) derived the weights $w_j(f_{t+1|t})$ of the Kalman filter analytically and showed that they vanish geometrically in a way that most recent values have more importance than older values. The weights are crucial because they determine how the new information is incorporated into the estimation of the state variable and, therefore, into the forecasts. Following Koopman and Harvey, the expression for the predicted state at time $t+1$ given the information at time t in our case is:

$$f_{t+1|t} = FK_t y_t + \sum_{j=1}^{t-1} FK_j y_j \prod_{i=j+1}^{t} F(I - K_i H) \tag{5.4}$$

where the K_j is the Kalman gain at time j and given by: $K_j = P_{j|j-1}H'(HP_{j|j-1}H' + R)^{-1}$. Notice that the Kalman gain depends inversely on the variance of the disturbances in the measurement equation R and also on the predicted state variance $P_{j|j-1}$, which is influenced by the initial state variance P_1 and the variances of the disturbances in the transition equations Q.

The forecasts of the variables at time $t+1$ given the information at time t are

$$y_{t+1|t} = Hf_{t+1|t} = HFK_t y_t + \sum_{j=1}^{t-1} HFK_j y_j \prod_{i=j+1}^{t} F(I - K_i H) \tag{5.5}$$

[3]It is important to take into account that this parametric method requires sufficient additional structure to ensure identification. See Stock and Watson (2004).

The first term of the summation is equivalent to the pooling term in Peña and Poncela (2004) and it is very important for the forecasts. The weight of this term depends on the signal-to-noise ratio (Q/R), the squared of the loading matrix (H) and whether the state variables are stationary or not (F).

The Kalman filter is designed in a way that it reaches the steady state in very few iterations and the Kalman gain will remain in its steady state value, which is constant. This creates problems in episodes of instability in variance. To understand why these models have problems to predict a recovery, suppose we are in the beginning of the recession and many variables drop dramatically. Assuming that the parameters are fixed or known, the forecast of the Kalman filter one period ahead will be driven mainly by the abnormal negative value of the last period, because past values and their weights are constant and neglectable. Over time, abnormal negative values will go to the second part of the sum, and even though their weights become smaller over time, they can still play an even more influential role than the most recent values. It is as if the model has lost memory and only the observations of the volatile period count. This is in agreement with Box-Steffensmeier and Lebo (2008) who demonstrated that methods like the Kalman filter or moving averages (i.e. rolling regressions or recursive regressions) in linear regression models cause problems with statistical inference and forecasting in presence of variance instability. They show that once the instability period is over, the model seems to lose its memory and does not use the past history any more. In other words, the most volatile part dominates and the model has only short-run memory.

On the other hand, imagine that one variable or a set of variables with a small Kalman gain or loading coefficients are among the first to signal the recession. Given that their weights are going to be constant and small, these atypical values will hardly have an effect on the forecasts. If the weights of the Kalman filter were not constant but instead updated, they would react in some episodes in a way that the model would not lose memory. One possible solution is to make the loading matrix time-varying. Alternatively, we could modify the filter in order to allow the Kalman gain to change over time. This is essentially what we do in the presence of missing values where the gain is fixed to zero for those observations with the aim of giving them null weight.

In practice, what is going to happen in most cases is that the maximum likelihood estimation accommodates the parameters to reach maximum in-sample fit. This can cause problems in out-of-sample forecasting. Furthermore, there can arise convergence problems because the likelihood function is flatter or its shape is complicated, for instance because of multiple modes. Additionally, we could get negative or zero values for the estimated variance of idiosyncratic factors (Sentana, 2000). These so-called Heywood cases may be caused by including too many or too few common factors, N and T being too small to provide stable estimates, a misspecified model, etc. The incidence of Heywood cases increases with the variance of the idiosyncratic components and the maximum likelihood method is especially vulnerable.

5.3.2. Proposed solution

One possible way of dealing with instability of second moments is to introduce time-varying parameters in the loadings matrix. However, in a model of unobserved components it would create further identification problems and some additional assumptions would be required. Alternatively, we could consider switching regimes in the common factor for the first and/or second moments (e.g. Camacho et al. 2012), but it might be difficult to determine the number of regimes and the pattern of switching. Instead we propose a more parsimonious solution that involves modeling the conditional variance of the innovations of the common factor Q_t. Introducing heteroscedasticity in factor models may improve forecasting and statistical inference because it is going to affect the signal-to-noise ratio which is crucial for forecasting and to identify the components. We will assume that Q_t follows either a GARCH or an Autoregressive Stochastic Volatility (ARSV) model. In this way the DFM implies the following conditional variance-covariance decomposition:

$$var_{t-1}(y_t) = HQ_tH' + R \tag{5.6}$$

but if the factors are covariance stationary (i.e. $E(Q_t) = Q$), we will have the same decomposition in unconditional terms:

$$E(\Sigma_t) = HE(Q_t)H' + R = HQH' + R \tag{5.7}$$

According to Sentana (1998) introducing heteroscedasticity in the common factors has interesting implications for the conditional correlation between two variables, which is given by:

$$\rho_{12t} = \frac{h_1 h_2 q_t}{\sqrt{(h_1^2 q_t + r_1)(h_2^2 q_t + r_2)}} \tag{5.8}$$

Introducing time-varying variance in the common factor q_t captures the aforementioned stylized facts: the volatility clustering, the commonality in volatility clustering and the relationship between variance and correlation. This is, that periods when the variables are more correlated coincide with those when the variance of the variables increase simultaneously. Notice that the correlation is strongly related to the signal-to-noise ratios q_t/r_1 and q_t/r_2.

5.4. Montecarlo Experiment

5.4.1. Factor GARCH

The first experiment we have performed is to simulate 100 times a DFM for four series (sample size 200) with only one common factor. The common factor and the idiosyncratic components follow AR(2) processes, but our results are not sensitive to this choice.The innovations of the common factor are conditionally heteroscedastic. In particular, they follow a GARCH(1,1):[4]

$$Q_t = (1 - \alpha - \beta) + \alpha u^2_{t-1|t-1} + \beta Q_{t-1} \tag{5.9}$$

We distinguish two cases: a) $\alpha = 0.3$,$\beta = 0.5$: persistent but smooth GARCH. b) $\alpha = 0.5$,$\beta = 0.3$: persistent but volatile conditional variance. With the simulated series we simultaneously estimate the parameters[5] and the conditional variances by ML. This increases the efficiency of the estimation, especially in large samples, although it is computationally more difficult. Alternatively, we could use a two-step procedure, but Engle and Sheppard (2001) concluded that these estimators are not fully efficient as they use limited information. Notice that in the estimation step we take the number of factors and the lags of the idiosyncratic errors and factors as known, although this is in practice an additional source of error.

Our interest is to study the one-step-ahead out-of-sample forecasting properties of factor GARCH when we compare it with a standard homoscedastic DFM. The results of the simulations are collected in Table 5.1. What we theoretically expect is that an incorrectly specified model such as the homoscedastic one does a bad job. In contrasts, what we obtain according to the root mean squared error (RMSE) is that on average it performs comparable with the factor GARCH. Possibly the reason for the similar forecasting abilities is that GARCH introduces an estimation bias because the GARCH parameters are not very precisely estimated. As shown by Fiorentini and Sentana (2001), β is much more imprecisely estimated than α. Apart from this reason, Bos and Koopman (2004) and Harvey et al. (1992) demonstrated that in this situation the Kalman filter is no more optimal because the filter is evaluating a likelihood that is not linear any more as some of the parameters depend on squared observations. So, in reality it is evaluating a quasi-likelihood function. Furthermore, the estimation of GARCH models is very sensitive to the existence of non-normal residuals, outliers and structural breaks.

[4] Notice that the model assumes that the unconditional variance is 1. As we use variance targeting proposed by Engle and Mezrich (1996), the conditional variance is expressed in terms of the unconditional variance.

[5] To guarantee positive variances we reparametrise the GARCH parameters in the following way: $\alpha = sin^2(\alpha^*)$ and $\beta = sin^2(\beta^*)(1 - \alpha)$. The initial value for Q_t is $Q_1 = E(Q_t)$.

Table 5.1.: Simulation exercise: Factor GARCH

(a) Persistent GARCH

RMSE one-period ahead

Estimated models	variable 1	variable 2	variable 3	variable 4	average
Homosc. DFM	0.65	0.61	1.14	1.10	0.88
Factor GARCH (real)	0.63	0.61	1.11	1.08	0.86
Factor SV	1.08	1.00	1.28	1.33	1.17

Note: ** corresponds to the significance level of 5% of the Clark and West (2005) forecast accuracy test.

(b) Volatile GARCH

RMSE one-period ahead

Estimated models	variable 1	variable 2	variable 3	variable 4	average
Homosc. DFM	0.71	0.66	1.15	1.07	0.90
Factor GARCH (real)	0.70	0.66	1.14	1.05	0.89
Factor SV	1.13	1.03	1.36	1.34	1.21

Note: ** corresponds to the significance level of 5% of the Clark and West (2005) forecast accuracy test.

We also compare the factor GARCH with the DFM including stochastic volatility that will be studied in the next subsection. The model with stochastic volatility performs worse. Moreover, the test of forecast accuracy developed by Clark and West (2007) does not reject in any case the null hypothesis that the forecast accuracy of the heteroscedastic models is similar to the one in the homoscedastic case.

5.4.2. Factor Stochastic Volatility

The shocks governing the volatility may not necessarily be the innovations of the common factor. Therefore, a natural step is to extend the model to account endogenously for other types of shocks. This is the case of the ARSV model. Empirically it has been found that a simple ARSV fits the data equally well as more heavily parameterized GARCH models. Apart from that, ARSV is more flexible than GARCH models, even though it requires simulation methods to estimate the unobserved innovation of the variances. The complexity of estimating these models introduces an additional estimation bias and the uncertainty in the estimation of the stochastic volatility must be taken into account inside the likelihood. This together with the fact that the model is no more linear and Gaussian gives as a result that there is no analytical expression for the likelihood, and thus, numerical methods are required to compute it. Regarding these methods, there are two approaches in the literature: the Monte Carlo Markov Chain (MCMC)[6] and the Sequential Monte Carlo (SMC)[7]

[6]See Robert and Casella (2004) for an overview of MCMC.

[7]See Doucet, De Freitas and Gordon (2001) and Creal (2009) for a survey of SMC methods, and Fernández-Villaverde and Rubio-Ramírez (2004) for an illustrative example.

simulation-based methods.

MCMC is an iterative algorithm and typically delivers smoothed estimates (i.e. smoothing algorithm as the estimations of the parameters and variables of interest are based on all the information available in the whole data set). In contrast, the SMC is a recursive algorithm which is more appropriate for real time or on-line analysis[8] (i.e. filtering algorithm). As noticed in Primiceri (2005), smoothed estimates are more efficient and suitable when our objective is to identify and estimate the evolution of unobservable states over time (e.g. identify structural shocks), whereas filtered estimates are better for forecasting. As the latter applies to our study, we consider simulation-based filtering SMC methods such as particle filters, which are also much easier to implement than MCMC methods.

The purpose of SMC methods is to sequentially update samples from posterior distributions via importance sampling and resampling techniques. According to Doucet, de Freitas and Gordon (2001) particle filters produce Monte Carlo approximations to posterior distributions by propagating simulated samples whose weights are updated against incoming observations and taking advantage of the state-space representations of dynamic models. Therefore, each particle is a sampled value of the state vectors and/or the parameters of interest. In the state-space framework, these filtering algorithms perform reasonably well at filtering states in non-linear and/or non-gaussian models. Actually Fernández-Villaverde and Rubio-Ramírez (2007) show how particle filtering is useful to estimate dynamic macroeconomic models, in particular, dynamic stochastic general equilibrium (DSGE) models because the economies can be non-linear and/or non-normal. Moreover particle filtering is a likelihood-based approach comparable to the Bayesian averaging, where the weights depend on the likelihood of each particle.

The most popular SMC filter is the Auxiliar Particle Filter (APF) of Pitt and Shephard (1999) that uses the optimal importance density to compute the importance weights in the sampling step. The optimality involves perfect adaptation of the algorithm. A similar but more efficient method is the Rao-Blackwellised Particle Filter (RBPF henceforth) (Chen and Liu, 2000; Andrieu and Docet, 2002). It is based on marginalization via Kalman Filter to reduce the Monte Carlo variation and improve numerical efficiency.

It is typically assumed that the parameters of the model (e.g. the loadings or the autoregressive parameters for the state factor in our DFMs) are known or given. In practice, however, these parameters are unknown and have to be estimated. This causes problems in the previous algorithms because they should sequentially update the parameters given the estimated filtered states, and viceversa, update the estimated filtered states given the estimated parameters. There are very few works that have dealt with this problem. One possible solution proposed by Aguilar and

[8] Notice that the filtered estimates of the volatilities in DFM-SV estimated by SMC are directly comparable to the estimated volatilities in the DFM-GARCH because both rely on past information.

West (2000) is to estimate the parameters and the states with MCMC methods (e.g. Gibbs sampling) to fit the model to historical data, and then to carry out sequential particle filtering only on the states to forecast given the parameters previously estimated by MCMC. The problem is that MCMC usually is computationally very intensive. Therefore, running MCMC each time a forecast exercise is performed is not very practical, especially for real time analysis. What is necessary is a method capable of modifying the filtered and predicted values fast and efficiently as new information arrives. In this line of reasoning, a few works have adapted the sequential filtering algorithms to allow for sequential parameter learning. This learning process is based on one idea introduced by Gordon et al. (1993) in a different context and consists in adding small random perturbances to the parameter draws. This is a way of introducing an artificial evolution to the parameter as if they were time-varying even though they are constant over time. In reality, what is changing is the estimation of the parameters given the states. As the introduction of these shocks can lead to problems in the precision of the inferences, Liu and West (2001) considered a kernel smoothing of the parameters. They impose a Gaussian kernel with a shrinkage rule for the mean value (kernel location) to reduce over-dispersion, and a scale of the kernel that is a function of the smoothing parameter.

The aforementioned work of Liu and West (2001) proposed a general algorithm that incorporates this kernel parameter learning into the APF. However, in this paper we instead use the RBPF, also known as *mixture Kalman Filter*. It is preferable because it combines the standard and popular Kalman filter with Gaussian mixtures. Given the characteristics of our state-space model (i.e. conditionally linear and Gaussian), it is more efficient and flexible to use this extended version of the Kalman filter because it easily accommodates departures from normality and non-linearities. More details on this algorithm can be found in the Appendix.

Nevertheless, it should be noticed that there is evidence showing that the APF, and to a lesser extent RBPF, could degenerate for sequential parameter learning and result in inaccuracies, especially for the variance of the innovations of the volatility. This parameter is crucial, not only for particle filtering but also for MCMC. As Liu and West (2001) commented: "Sequential simulation-based filtering methods must always be combined with some form of periodic recalibration based on off-line analysis performed with much more computational time available than the filtering methods are designed to accommodate". They propose to monitor the learning process of the parameters and compare it with their values when the model is estimated by MCMC. But as in some cases the problem of parameter degeneracy is very serious, they also suggested to use the parameter values obtained by MCMC or Maximum Likelihood (also known as off-line methods) to avoid inaccuracies.

Additionally, when the number of parameters is very high, this problem could become so important that it leads to a *sample impoverishment* or *depletion*. The reason is that due to the high variance of the importance weights over time, very few particles are used in each iteration to approximate the posterior distribution. Because of that, it is necessary to monitor that there is no weight degeneracy or that the number of dead particles is not very high. In order to do that we compute several measures such as: i) the *survival rate*, $SR_t = (1 - N_t)/D$, where N_t is the number of non-selected particles at time t and D the number of total particles; ii) the *effective sample size* (Liu, 1996), $ESSt = (1/\sum_{i=1}^{D} w_t^{(i)2})^{-1}$ where $w_t^{(i)}$ is the importance weight of particle i at time t; and iii) the *Shannon entropy*, $SE_t = -\sum_{i=1}^{D} w_t^{(i)} ln(w_t^{(i)})$. We have to check for instance that the survival rate or the entropy do not decrease over time, and the effective sample size is not lower than 60-80% of the total particles generated. In practice, the performance of the parameter learning requires a bit of tuning of the width of the kernel and the variance of the artificial noise.

Now we repeat the same forecasting experiment performed in the previous subsection. First, we simulate 100 times a DFM for four series (sample size 200) and one common factor. But this time the innovations of the factor follow the SV model

$$ln(Q_t) = ln(Q_{t-1}) + w_t \tag{5.10}$$

Then, we estimate again 3 models: the homoscedastic DFM, the DFM with factor GARCH, and the DFM with factor SV[9]. The results are displayed in Table 5.2. In contrast to the GARCH case, this time the SV clearly outperforms the GARCH and the homoscedastic models. In fact, the test of forecast accuracy does not support the hypothesis that the homoscedastic model performs similar at forecasting. Nevertheless, although it is not shown, notice that in the SV model the parameters are estimated with a small bias due to the kernel smoothing method.

Table 5.2.: Simulation exercise: Factor SV

RMSE one-period ahead

Estimated models	variable 1	variable 2	variable 3	variable 4	average
Homosc. DFM	2.25	2.37	2.59	2.72	2.48
Factor GARCH	2.13	2.20	2.46	2.58	2.34
Factor SV (real)	1.92**	1.98**	2.39**	2.34**	2.16**

Note: ** corresponds to the significance level of 5% of the Clark and West (2005) forecast accuracy test.

5.5. Empirical Application: Stock and Watson's (1991) DFM

Stock and Watson (SW, 1991) proposed a simple DFM to estimate a coincident indicator of the economic activity for the United States from four monthly series.

[9] The resampling method used is the stratified sampling, and the discount factor in the parameter learning algorithm is 0.9. Different resampling methods and values of the discount factor led to very similar results.

These series are carefully monitored by the NBER in order to date a chronology of the peaks and troughs, or beginning of recessions and expansions. This model became very popular to construct business cycle indicators and has subsequently been extended by Kim and Nelson (1999) and Mariano and Murasawa (2003). However, Stock and Watson (2008) showed in their work about forecasting with DFM in presence of instabilities that the estimates of the common factor are quite stable and, in contrast, the estimates of the loadings or regression coefficients are quite unstable. Therefore, they concluded that the best strategy to produce accurate forecasts in this framework is to use estimates of the common factors using the full sample, and estimates of the loadings using only a sub-sample or time-varying estimations. This is related to the idea that the best predictors are not always the same indicators or, in other words, the time-varying relationship among variables. Later on many subsequent papers considered a large number of indicators because large cross-sections provide insurance against structural instabilities.

Using the same specification as SW(1991) and our proposed extensions, we perform next a forecasting exercise out-of-sample and in pseudo real time. We predict one-period ahead from 1994.01 until 2011.04, re-estimating the model each period but using the last vintage of data available (May 2011). The results are collected in Table 5.3.

Table 5.3.: Forecasting exercise with Stock and Watson's (1991) DFM

(a) Period 1994.01-2011.05

	IPI		INC		SALES		EMP		Average	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Homosc. DFM	0.93	0.67	0.46	0.43	1.54	0.95	0.02	0.12	0.74	0.54
Factor GARCH	0.90	0.65	0.45	0.43	1.51	0.93	0.02	0.12	0.72	0.53
Factor SV	0.49	0.50	0.28	0.33	0.79	0.67	0.03	0.15	0.40	0.41

(b) Great recession

	IPI		INC		SALES		EMP		Average	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Homosc. DFM	3.94	1.51	0.59	0.61	1.71	1.03	0.07	0.20	1.58	0.84
Factor GARCH	3.93	1.51	0.57	0.59	1.75	1.06	0.07	0.20	1.58	0.84
Factor SV	1.96	1.00	0.37	0.49	1.02	0.82	0.10	0.30	0.86	0.65

We see that introducing stochastic volatility in the common factor reduces the one-step-ahead mean squared error (MSE) and the mean absolute error (MAE) when we consider the whole period, 1994.01-2011.04, and especially for the great recession, 2007.12-2009.06. In contrast, introducing GARCH does not lead to significant forecasting improvements.

We also compute forecast accuracy tests to compare all the specifications with the homoscedastic DFM. There are two well-known one-sided tests in the literature: Diebold and Mariano (1995) and Clark and West (2007). The former is very popular because it is very robust to non-quadratic loss functions and when the forecast errors are non-gaussian or have non-zero mean or under serial and contemporaneous correlation. However, it is more suitable to test forecast accuracy in non-nested models and it does not take into account the noise introduced by the estimation of parameters. In order to do that the second test introduces a correction term. Apart from that, Clark and West's test is designed to forecast evaluation in nested models, as in our case. It compares a small model with a larger one which encompasses it. The results of Clark and West's test are collected on Table 5.4. Notice that to compute it we assume a quadratic loss function and asymptotic normality of the computed statistic, and we use Barlett's window to compute the long-run variance together with the optimal lag truncation parameter suggested by Newey and West (1994).

Table 5.4.: P-values from the Clark and West (2007) forecast accuracy test

(a) Period: 1994-2011

	IPI	INC	SALES	EMP
Factor GARCH	0.25	0.15	0.00	0.01
Factor SV	0.00	0.01	0.00	0.00

(b) Great recession

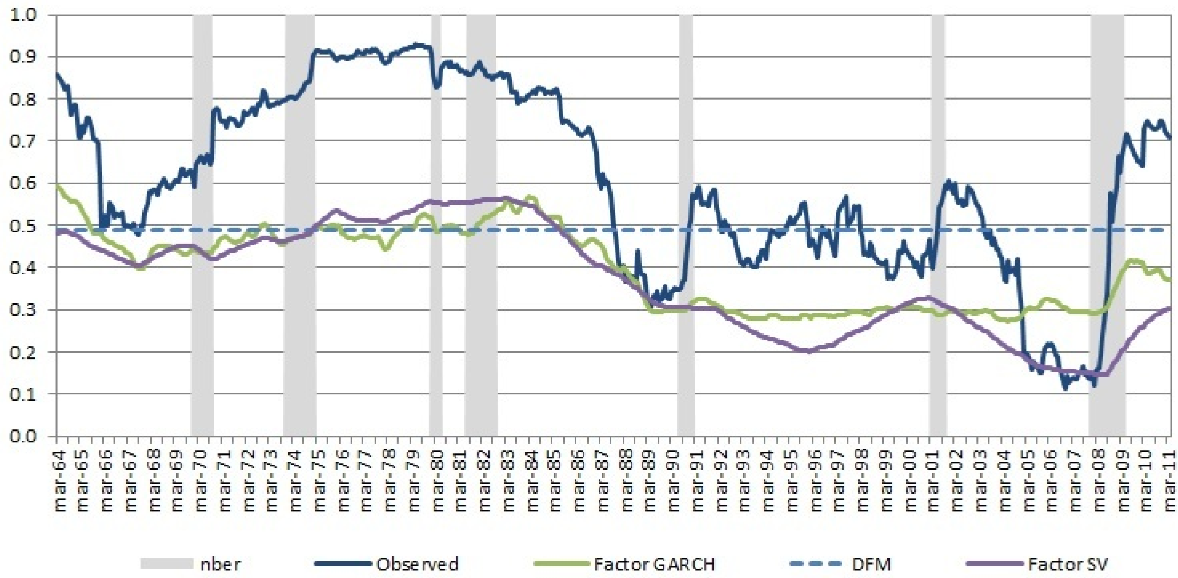
	IPI	INC	SALES	EMP
Factor GARCH	0.38	0.18	0.29	0.33
Factor SV	0.00	0.00	0.00	0.00

Considering both the MSE and the statistical test, we can conclude that in general the models with heteroscedasticity in the common factor improve the forecast accuracy for most of the series and also during the great recession. However, as stressed by Diebold and Mariano, it is important to consider that the superiority of a particular model in terms of forecasts accuracy does not necessarily imply that forecasts from other models contain no additional information. Therefore, our conclusion does not mean that the forecasts of the homoscedastic DFM are wrong or not informative at all. But in specific situations such as in a very serious crisis like the great recession, or when the level of uncertainty is very high, it could be worth to consider heteroscedastic models.

As we are going to see next, there are some additional advantages of our approach. First, it is straightforward to obtain the implicit correlations. For simplicity we have computed once more our measure of comovement with the estimated correlations that is directly comparable with the recursive measure computed before.

In Figure 5.3 we see that in all cases we observe an inverse S shape. This means that the correlations would have been higher in the beginning and would have gone down with the great moderation. Nevertheless, there are some symptoms of increasing correlation in the last part of the sample. This is in stark contrast with the constant correlation assumption in the standard DFMs.

Figure 5.3.: Dynamic correlations



As a useful by-product of our approach we get an estimate of the volatility of the common factor, which in this business cycle model can be interpreted as a measure of the broad macroeconomic risk. The GARCH and SV (filtered) estimates of the common factor's volatility are displayed in Figure 5.4. It picks up the two facts mentioned before: the great moderation and the higher volatility during the recessions. Notice that both measures are realized volatilities as they are filtered estimations.

We have performed the exercise of estimating the smoothed volatility in the DFM with stochastic volatility in the common factor by MCMC methods which is displayed in Figure 5.5. We observe the same pattern as before in the filtered volatility but in an even clearer way.

Figure 5.4.: Common factor conditional variance. Filtered values

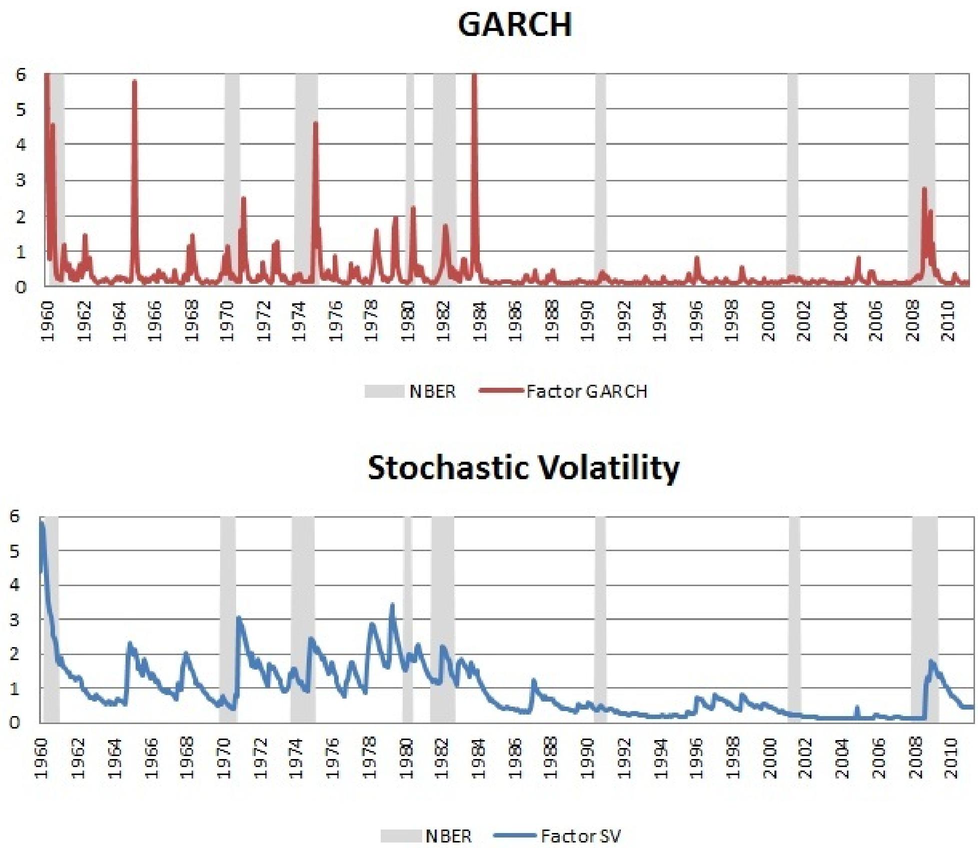
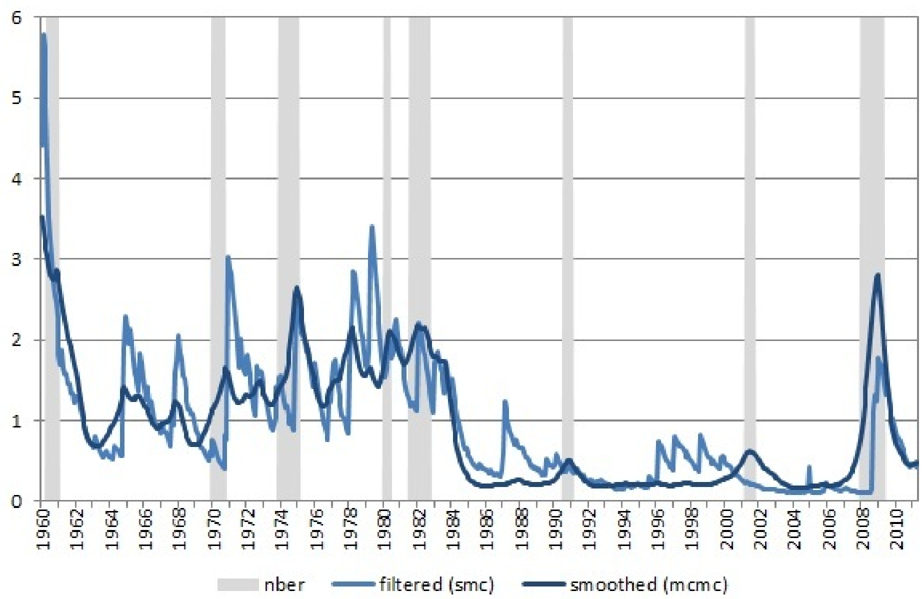
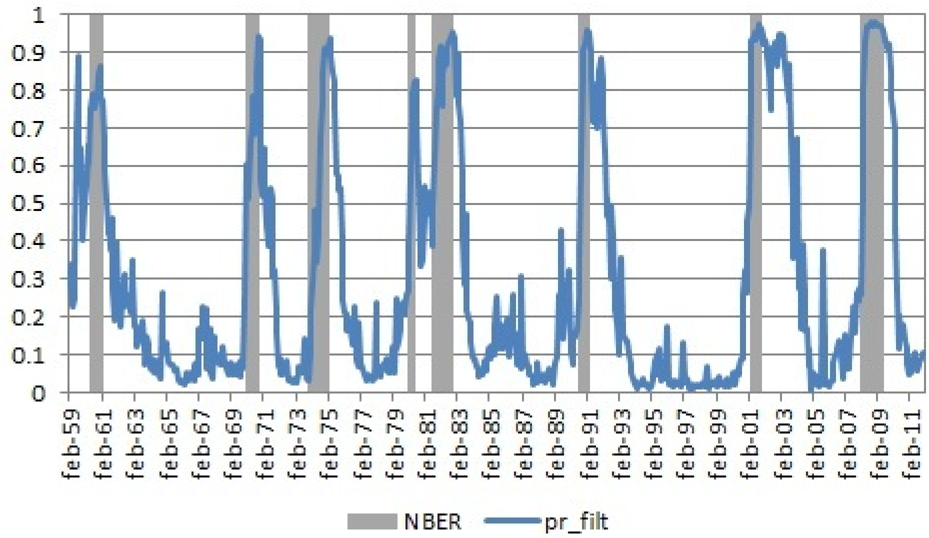


Figure 5.5.: Common factor conditional variance. Smoothed values



One advantage more of our SMC method is that as it is designed for non-linear or non-gaussian models, it is straightforward to introduce additional non-linearities in our DFM-SV. In this way, we have estimated the model considering Markov Switching in the mean of the factor, with two states corresponding to expansion and recession. It is also straightforward to obtain the probability of being in recession as it is shown in Figure 5.6. The periods when the probabilities of recession are near one coincide very closely with the official recessions dated by the NBER (shaded areas). We also observe that the model has more difficulties to signal the exit of the recessive phase in the last 3 recessions, characterized by jobless recoveries.

Figure 5.6.: Filtered probabilities of recession



5.6. Conclusions

Episodes such as the recent Great Recession and moments of especially high uncertainty have underlined the necessity of considering the changing level of uncertainty in models for forecasting in macroeconomics such as the DFM. In this work we have extended the standard DFM in a parsimonious way to take into account time-varying correlations and variances. We do this by introducing heteroscedasticity (i.e. GARCH or ARSV) in the common factor. We have also proposed a sequential Monte Carlo method to estimate stochastic volatility in DFM, easier to implement than MCMC and, therefore, more appropriate for performing forecasting exercises. Additionally, this method is fast, efficient and robust to non-linearities and departures from gaussianity. Furthermore, we have shown that the heteroscedastic models have better forecasting properties at short-run (one period ahead) than homoscedastic models, especially in these specific episodes. Apart from that, it takes the time-varying correlations between variables into account and delivers the volatility of the common factor which we can interpret as an indicator of global macroeconomic risk. Finally, it is possible to extend these models for additional non-linearities such as markov switching in the mean of the factor to compute probabilities of being in recessions or expansions.

Regarding our proposed method to introduce SV in DFM, it has however some shortcomings that must be considered. There could arise problems with the parameter learning, especially when the number of parameters is very high, the learning process is too slow or the priors are not very realistic. The problem is that how to choose effective particles still lacks of rigorous justification. And in some cases it could happen that the Monte Carlo error grows exponentially. Although there are some recent proposals in the literature to improve this methodology, there is no agreement on which is the best one. Most of them try to improve SMC by introducing MCMC steps. This requires further research.

One step ahead in our research agenda is to extend these models to real-time data. These datasets have interesting characteristics: the data have mixed frequencies, missing observations, and ragged-ends, because the indicators are not released at the same time. And therefore, the level of uncertainty is higher and the variance problems are even more relevant. Nevertheless, to adapt the SMC methods is complicated because the number of missing data is crucial. When the rate of missing data increases, it is harder to achieve a certain tolerance and a large number of particles is needed.

6. Conclusions

In this dissertation I provide evidence that the business cycles have hardly changed with the monetary union given that the exchange rate stability has not implied either considerable convergence in business cycle characteristics or in synchronization. I show that the international economies seem to be less synchronized in the last fifteen years (until 2004) and find evidence against the existence of just one common European cycle. In other words, the European economies are not so synchronized or do not have cycles whose length, depth and shape are so similar to consider that there exists one cycle representative of the whole EU or the EMU.

Furthermore, I have shown that the linkages across Euro area economies existed already prior to the establishment of the union. In this sense, the smooth transition towards a more integrated economic area could be due to previous strong business cycles correlations and linkages, fundamentally through trade. This is not the case of the last enlargements in 2004 and 2007 because the differences among the new members and the old members, and also among themselves, are much more important than the differences that the old members exhibited before the establishment of the union.

I find a role for different macroeconomic variables in explaining the comovements across economies. Apart from trade, there is a significant contribution from other macroeconomic, structural and economic policy variables, like specialization in production, labor productivity or fiscal policy, to explain business cycle comovements.

All these results point to the existence of persistent cyclical divergences and structural and institutional differences (e.g. labor productivity) across European countries. This makes it more likely that asymmetric shocks or shocks with asymmetric effects happen and creates difficulties for the decision-making on the appropriate monetary policy stance to accommodate them. Indeed, this is what we have seen with the recent great recession. This crisis is an example of a symmetric shock with asymmetric effects. And it has shown that there are still important structural divergences and that more mechanisms are needed to deal with this type of shocks.

Last, but not least, the Great Recession has changed the observed trend of smoother cycles in the United States and in most of the EU countries since the beginning of the 1980s, the so-called Great Moderation. Moreover, it has shown that the relationships between the economic variables are not constant over time and along the cycle, especially in the recessions. I have identified several stylized facts regarding the correlation and variance of several macroeconomic variables that describe very well the business cycles in the US. These facts are: i) an important correlation or comovement among many macroeconomic variables; ii) volatility clustering, or moments of high variance that alternate with moments of low variance or, in other words, that the level of uncertainty or macroeconomic risk is not constant over time; iii) volatility comovement or that the movements in volatility happen simultaneously; iv) leverage or asymmetric effect, in the sense that during the recessions the variance and the correlations are higher than during the expansions. The main conclusion is that periods of high volatility or uncertainty like the recessions are accompanied by high correlations. I have modified a simple dynamic factor model using a very parsimonious solution to take these facts into account. Furthermore, the proposed solution improves the forecasting performance in the short-run, especially in moments of high uncertainty. And it also delivers the volatility of the common factor which in this context can be interpreted as an indicator of global macroeconomic risk.

Conclusiones

En esta tesis muestro evidencia de que los ciclos económicos apenas han cambiado con la unión monetaria puesto que la estabilidad del tipo de cambio no ha implicado una convergencia considerable ni en las características de los ciclos ni en la sincronía cíclica. Muestro que las economías parecen menos sincronizadas en los últimos quince años (hasta 2004) y encuentro evidencia en contra de la existencia de un ciclo común europeo. En otras palabras, las economías europeas no están tan sincronizadas o no tienen ciclos cuya longitud, profundidad y forma sea tan parecida como para considerar que existe un ciclo representativo de toda la UE o de la UME.

Además, he mostrado que los vínculos entre las economías del área del Euro fundamentalmente existían antes del establecimiento de la unión. En este sentido, la transición suave hacia una área económicamente más integrada podría deberse a la existencia fuertes correlaciones previas entre los ciclos económicos y de vínculos, principalmente a través del comercio. Este no ha sido el caso de las ampliaciones de 2004 y 2007 porque las diferencias entre los nuevos miembros con los antiguos miembros, y también entre ellos, son mucho más importantes que las diferencias de los antiguos miembros tenían antes del establecimiento de la unión.

Encuentro un papel para las diferentes variables macroeconómicas en explicar los comovimientos entre las economías. Además del comercio, hay una contribución significativa de otras variables macroeconómicas, estructurales y de política económica, tales como la especialización productiva, la productividad del trabajo o política fiscal, para explicar los comovimientos cíclicos.

Estos resultados apuntan a la existencia de persistentes divergencias cíclicas y diferencias estructurales e institucionales (por ejemplo, en la productividad laboral) entre las economías europeas. Y ésto hace más probable que ocurran perturbaciones asimétricas o perturbaciones con efectos asimétricos y plantea dificultades para la toma de decisiones sobre la postura apropiada de política monetaria para acomodarlas. De hecho, esto es lo que hemos visto con la reciente gran recesión. Esta crisis es un ejemplo de una perturbación simétrica con efectos asimétricos. Y ha demostrado que hay todavía importantes divergencias estructurales y que son necesarios más mecanismos para hacer frente a este tipo de perturbaciones.

Por último, pero no por ello menos importante, la Gran Recesión ha cambiado la tendencia de suavizamiento del ciclo observada tanto en EE.UU. como en la UE desde principios de los años ochenta, la llamada Gran Moderación. Además, ha mostrado que las relaciones entre las variables económicas no son constantes tanto en el tiempo como a lo largo del ciclo, especialmente en las recesiones. He identificado varios hechos estilizados en relación a la correlación y varianza de varias variables macroeconómicas que describen muy bien los ciclos económicos en EE.UU. Estos hechos son: i) una importante correlación o comovimiento entre muchas variables macroeconómicas; ii) agrupamiento de volatilidad, o momentos de alta varianza que se alternan con momentos de baja varianza, o en otras palabras, que el nivel de incertidumbre o riesgo macroeconómico no es constante en el tiempo; iii) comovimiento en la volatilidad o que los movimientos en la volatilidad ocurren simultáneamente; iv) efecto asimétrico o de apalancamiento, en el sentido de que durante las recesiones la varianza y las correlaciones son mayores que durante las expansiones. La principal conclusion es que periodos de alta volatilidad o incertidumbre como las recesiones van acompañados de elevadas correlaciones. He modificado un simple modelo factorial dinámico usando una solución muy parsimoniosa para tener en cuenta estos hechos. Además, la solución propuesta mejora la calidad de las predicciones en el corto plazo, especialmente en momentos de alta incertidumbre. Y también se obtiene como resultado la volatilidad del factor común, que en este contexto se puede interpretar como un indicador de riesgo macroeconómico global.

A. Appendix to Chapter 2

Figure A.1.: Industrial production indexes: EMU-12 countries

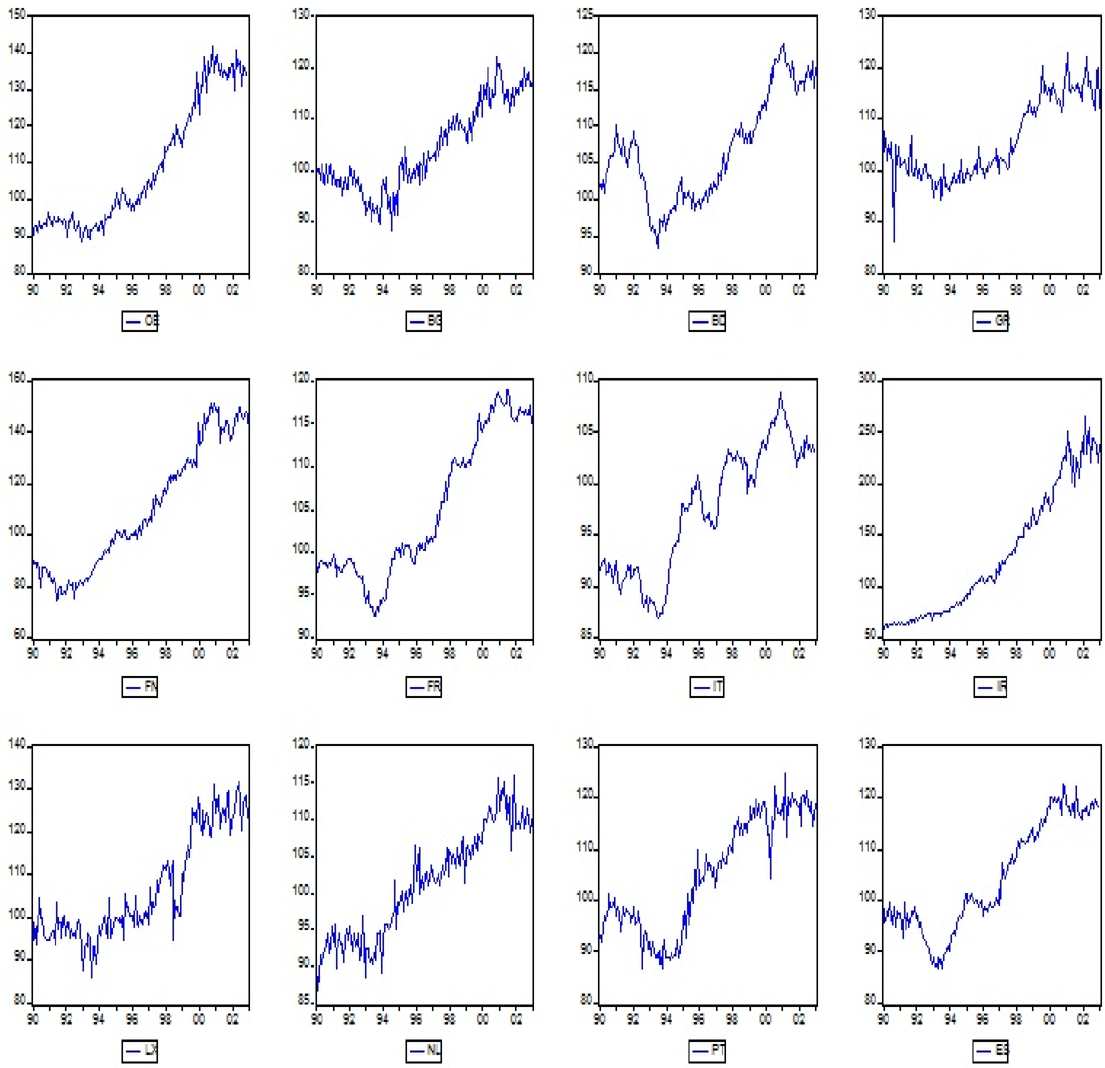


Figure A.2.: Industrial production indexes: some industrialized countries

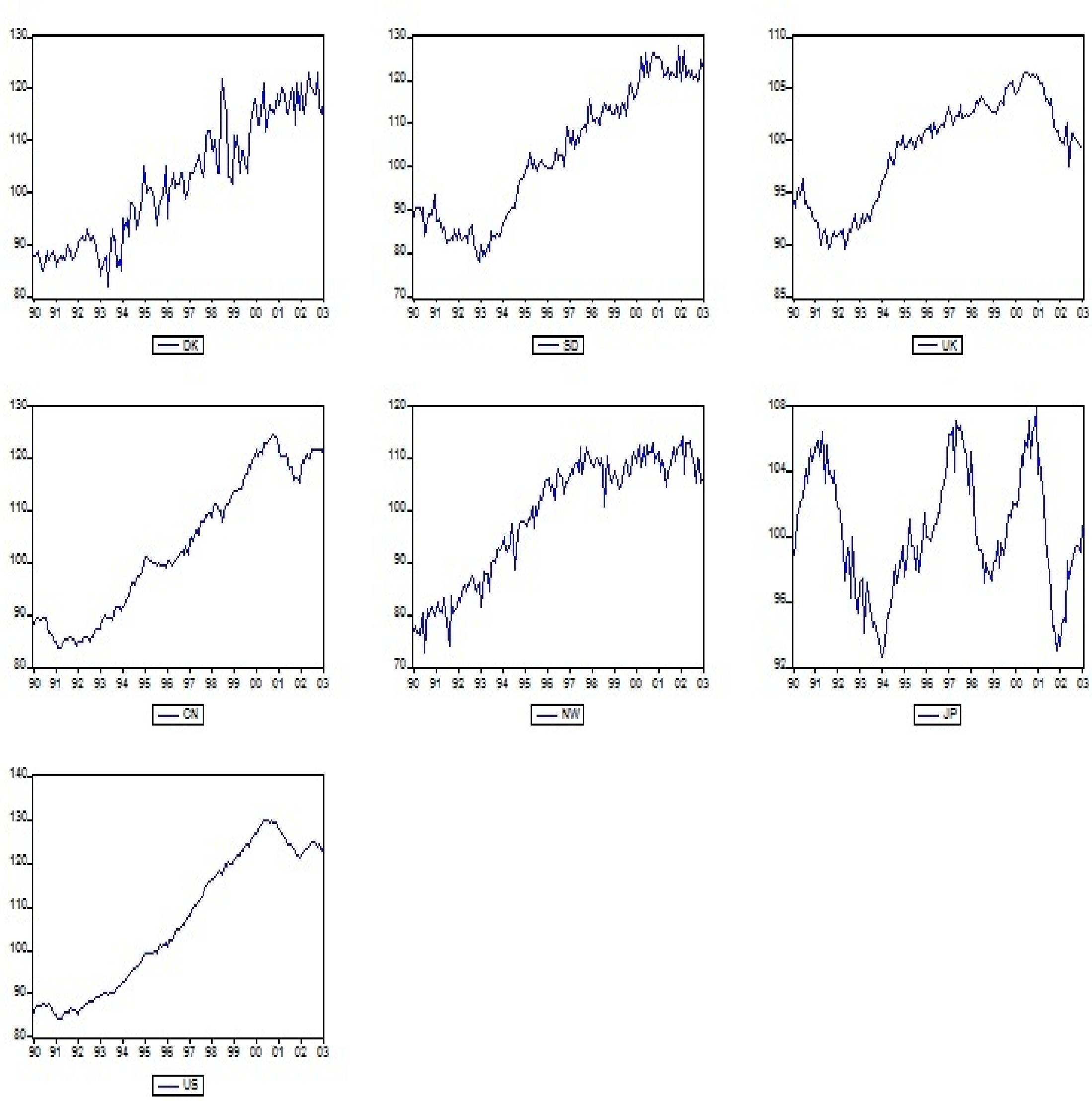


Figure A.3.: Industrial production index: accession countries

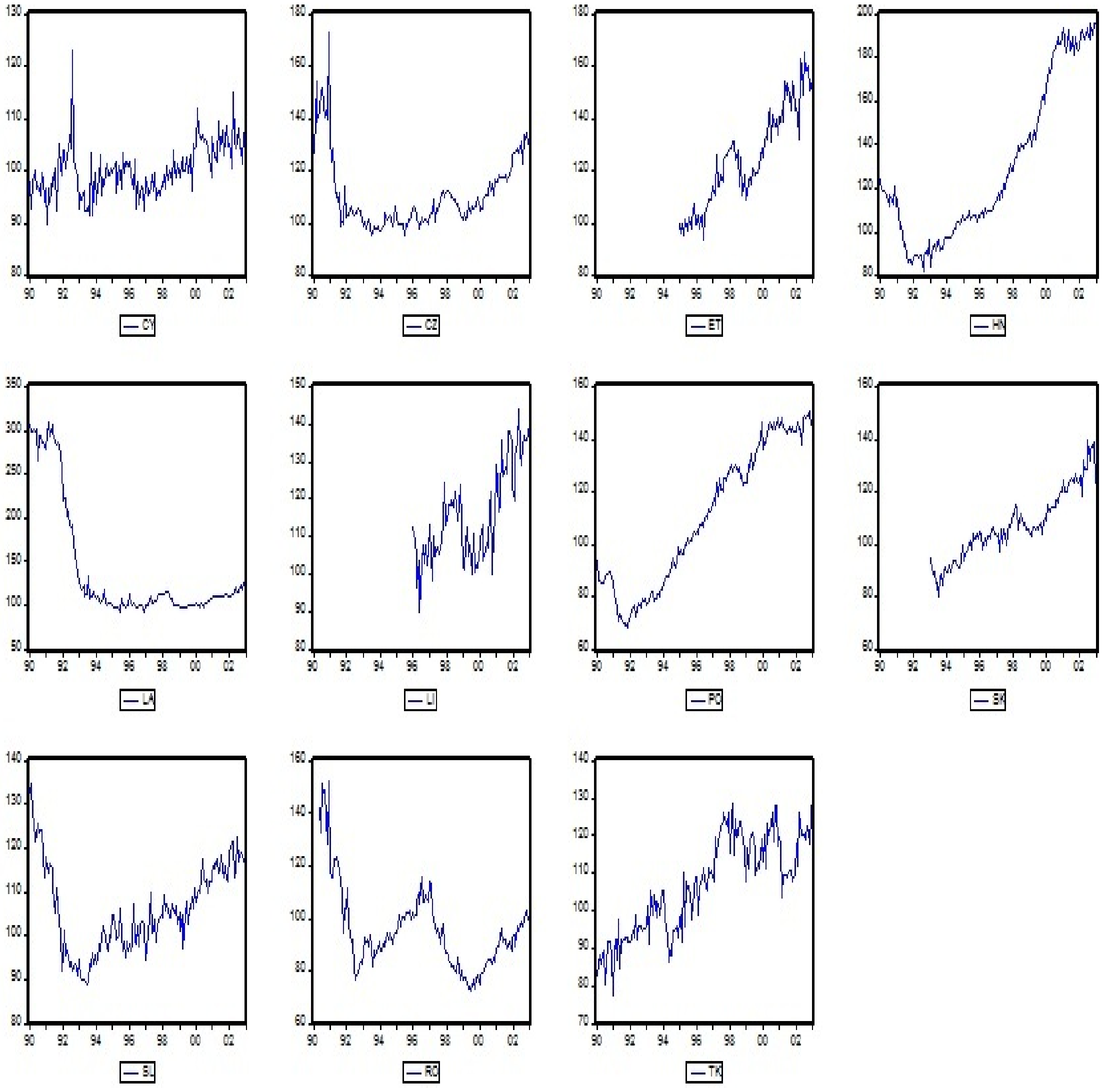


Table A.1.: Distances based on measure 1

	Austria	Belgium	Germany	Greece	Finland	France	Italy	Luxemburg	Netherland	Portugal	Sweden	UK	Canada	Norway	Japan	USA	Spain	Denmark	Ireland	Cyprus	Czech	Hungary	Latvia	Poland	Slovenia	Turkey	Romania	Slovakia	Estonia	Lithuania
Austria	-	0.27	0.15	0.45	0.73	0.49	0.53	0.87	0.45	0.98	0.27	0.86	0.37	0.97	0.64	0.52	0.26	0.43	0.36	1.15	0.95	0.21	1.02	0.46	0.41	0.80	1.29	0.87	0.81	0.03
Belgium		-	0.36	0.57	0.59	0.51	0.42	0.43	0.49	0.49	0.52	0.82	0.85	0.62	0.35	0.45	0.40	0.57	0.51	1.13	1.18	0.54	0.80	0.59	0.54	0.82	1.15	0.62	0.75	0.35
Germany			-	0.72	0.68	0.18	0.61	0.80	0.40	0.87	0.47	0.62	0.86	0.84	0.40	0.55	0.58	0.47	0.75	0.90	0.78	0.65	0.75	0.87	0.40	1.00	1.40	0.70	0.38	0.45
Greece				-	0.86	0.38	0.84	0.68	0.83	1.02	0.73	0.81	1.03	1.04	0.96	0.68	0.82	0.92	0.48	0.85	0.96	0.91	1.11	0.88	0.95	1.19	1.18	1.21	1.16	0.48
Finland					-	0.58	0.65	0.89	1.18	0.84	0.25	0.70	0.23	0.77	0.46	0.49	0.50	0.83	1.00	0.84	1.02	0.22	0.88	0.84	0.77	0.69	1.37	0.73	0.77	0.99
France						-	0.45	0.67	0.41	0.80	0.82	0.59	0.54	0.95	0.57	0.46	0.47	0.35	0.77	1.09	0.79	0.46	0.93	0.89	0.55	0.94	1.35	0.88	0.81	0.94
Italy							-	0.74	0.41	0.76	0.69	0.48	0.44	0.78	0.35	0.56	0.40	0.61	0.64	0.97	0.54	0.56	0.46	0.51	0.67	0.86	1.11	0.69	0.55	0.69
Luxemburg								-	0.84	0.82	1.03	0.80	0.64	0.83	0.64	0.82	0.76	0.81	0.83	0.99	0.77	0.83	0.64	0.60	1.09	1.13	1.22	0.83	0.59	1.20
Netherland									-	1.10	0.68	0.63	0.79	0.93	0.59	0.79	0.45	0.56	0.81	0.83	0.89	0.61	0.92	0.94	0.68	1.11	1.14	0.89	0.81	1.31
Portugal										-	1.25	1.11	0.85	0.95	0.86	0.92	0.97	1.01	0.89	0.83	0.90	1.09	0.85	0.88	1.14	0.87	1.12	0.87	0.91	1.31
Sweden											-	0.58	0.76	0.77	0.45	0.68	0.31	0.59	0.58	0.99	1.24	0.80	1.19	0.82	0.41	0.96	0.95	0.74	1.15	1.14
UK												-	0.22	0.69	0.53	0.34	0.77	0.71	0.62	0.93	1.06	0.58	1.14	0.25	0.65	1.04	1.11	1.05	0.85	1.05
Canada													-	0.92	0.22	0.19	0.71	0.71	0.61	0.98	0.79	0.26	1.02	0.29	0.77	0.98	1.03	0.88	0.72	1.11
Norway														-	1.07	0.87	0.92	0.85	0.94	1.01	0.96	0.98	0.77	0.79	0.97	0.78	1.11	0.80	0.81	1.18
Japan															-	0.30	0.46	0.84	0.68	1.17	0.67	0.60	0.85	0.33	0.81	0.65	0.65	1.02	0.58	0.78
USA																-	0.59	0.66	0.59	0.82	1.13	0.32	1.07	0.35	0.74	0.70	1.42	0.90	0.59	0.97
Spain																	-	0.35	0.63	0.94	0.77	0.43	0.60	0.68	0.42	0.84	1.35	1.02	0.68	1.16
Denmark																		-	0.79	0.66	0.84	0.70	0.74	0.55	0.29	1.15	0.98	0.65	0.62	1.15
Ireland																			-	1.14	0.89	0.86	0.95	0.96	0.78	0.86	1.09	0.89	1.14	1.06
Cyprus																				-	0.90	0.63	1.01	1.19	0.75	1.00	1.20	0.72	0.61	1.19
Czech																					-	0.84	0.54	0.60	0.65	1.01	0.97	0.80	0.49	1.29
Hungary																						-	1.11	0.80	0.72	0.91	1.12	0.85	0.64	1.17
Latvia																							-	0.86	0.82	1.07	1.01	0.68	0.53	1.28
Poland																								-	0.50	0.76	1.02	0.83	0.46	1.06
Slovenia																									-	1.04	0.90	0.53	0.79	0.95
Turkey																										-	1.06	0.95	0.90	0.93
Romania																											-	0.48	0.77	0.54
Slovakia																												-	0.31	0.41
Estonia																													-	0.49
Lithuania																														-

Table A.2.: Distances based on measure 2

	Austria	Belgium	Germany	Greece	Finland	France	Italy	Luxemburg	Netherland	Portugal	Sweden	UK	Canada	Norway	Japan	USA	Spain	Denmark	Ireland	Cyprus	Czech	Hungary	Latvia	Poland	Slovenia	Turkey	Romania	Slovakia	Estonia	Lithuania
Austria	-	0.39	0.21	0.82	0.44	0.21	0.31	0.60	0.45	0.77	0.16	0.52	0.55	0.86	0.48	0.52	0.26	0.44	0.55	0.62	0.71	0.18	0.83	0.39	0.33	0.95	0.99	0.67	0.58	0.96
Belgium		-	0.38	0.94	0.63	0.44	0.33	0.62	0.57	0.77	0.45	0.74	0.68	0.63	0.55	0.60	0.42	0.40	0.46	0.59	0.64	0.47	0.63	0.36	0.45	0.67	0.80	0.52	0.49	0.92
Germany			-	0.93	0.67	0.16	0.29	0.64	0.26	0.68	0.31	0.70	0.84	0.82	0.41	0.74	0.21	0.33	0.66	0.45	0.50	0.32	0.56	0.30	0.20	1.05	0.79	0.61	0.37	0.79
Greece				-	1.06	0.76	0.89	0.93	0.95	0.87	0.90	0.98	1.00	1.30	1.28	1.07	0.77	0.86	0.78	0.64	1.11	0.98	1.19	1.18	0.86	1.42	1.33	1.07	1.47	1.00
Finland					-	0.56	0.53	0.85	0.78	1.23	0.35	0.20	0.26	0.77	0.69	0.27	0.58	0.65	0.65	0.97	0.80	0.20	0.82	0.56	0.48	0.87	1.06	0.77	0.59	0.98
France						-	0.17	0.54	0.38	0.73	0.28	0.57	0.66	0.97	0.65	0.63	0.13	0.29	0.59	0.47	0.48	0.33	0.46	0.38	0.25	1.21	1.01	0.59	0.48	0.61
Italy							-	0.50	0.36	0.77	0.31	0.54	0.51	0.81	0.52	0.54	0.19	0.34	0.39	0.55	0.46	0.29	0.47	0.30	0.41	0.98	0.87	0.48	0.46	0.80
Luxemburg								-	0.72	0.90	0.67	0.67	0.60	0.75	0.59	0.65	0.53	0.70	0.86	0.72	0.70	0.68	0.81	0.33	0.73	1.12	1.03	0.88	0.65	1.34
Netherland									-	0.56	0.40	0.61	0.95	0.78	0.53	0.90	0.47	0.50	0.60	0.55	0.68	0.51	0.78	0.57	0.49	1.26	0.65	0.57	0.82	0.83
Portugal										-	0.77	1.16	1.36	0.97	0.93	1.28	0.83	0.96	0.66	0.74	0.97	1.21	0.92	1.05	1.04	1.04	0.79	0.68	1.35	0.86
Sweden											-	0.42	0.57	0.68	0.53	0.60	0.27	0.42	0.58	0.59	0.71	0.34	0.87	0.50	0.31	1.08	0.83	0.73	0.62	0.94
UK												-	0.29	0.87	0.62	0.30	0.62	0.70	0.73	0.94	0.89	0.29	0.97	0.50	0.55	1.22	0.90	0.83	0.70	1.18
Canada													-	0.98	0.56	0.10	0.58	0.77	0.72	1.00	0.91	0.27	1.04	0.50	0.67	0.84	1.08	0.95	0.74	1.45
Norway														-	0.82	0.93	0.94	0.68	0.89	0.72	0.62	0.87	0.71	0.60	0.75	0.63	0.83	0.87	0.58	1.05
Japan															-	0.54	0.59	0.75	0.82	0.97	0.78	0.49	0.98	0.29	0.72	0.73	0.54	0.80	0.60	1.39
USA																-	0.63	0.72	0.69	0.87	0.82	0.26	0.96	0.40	0.70	0.70	1.16	0.87	0.65	1.30
Spain																	-	0.34	0.70	0.48	0.68	0.37	0.71	0.47	0.27	1.16	1.02	0.78	0.58	0.94
Denmark																		-	0.75	0.43	0.42	0.48	0.47	0.41	0.24	1.09	0.92	0.68	0.41	0.67
Ireland																			-	0.77	0.68	0.54	0.75	0.71	0.79	0.80	1.00	0.59	0.92	0.87
Cyprus																				-	0.77	0.80	1.08	0.71	0.59	1.18	1.17	0.83	0.97	1.05
Czech																					-	0.71	0.11	0.36	0.53	0.79	1.01	0.48	0.27	0.42
Hungary																						-	0.77	0.38	0.42	0.87	0.94	0.75	0.53	0.96
Latvia																							-	0.49	0.63	0.63	1.03	0.32	0.27	0.30
Poland																								-	0.47	0.79	0.81	0.56	0.24	1.03
Slovenia																									-	1.18	0.78	0.69	0.43	0.64
Turkey																										-	1.00	0.84	0.55	0.98
Romania																											-	0.66	0.77	1.01
Slovakia																												-	0.35	0.38
Estonia																													-	0.53
Lithuania																														-

Table A.3.: Distances based on measure 3

	Austria	Belgium	Germany	Greece	Finland	France	Italy	Luxemburg	Netherland	Portugal	Sweden	UK	Canada	Norway	Japan	USA	Spain	Denmark	Ireland	Cyprus	Czech	Hungary	Latvia	Poland	Slovenia	Turkey	Romania	Slovakia	Estonia	Lithuania
Austria	-	0.75	0.57	0.80	0.87	0.36	0.66	0.54	0.33	0.69	0.64	0.94	0.86	0.89	0.62	0.91	0.49	0.57	0.73	0.70	0.91	0.64	1.31	0.97	0.62	1.20	1.19	0.94	1.21	1.11
Belgium		-	0.57	0.74	0.86	0.62	0.54	0.71	0.70	0.65	0.43	0.69	0.70	1.02	0.64	0.76	0.41	0.74	0.77	0.98	0.55	0.61	0.90	0.68	0.53	0.87	0.92	0.46	0.62	1.00
Germany			-	1.16	0.94	0.29	0.75	0.92	0.56	0.93	0.80	0.96	0.78	1.00	0.67	0.92	0.57	0.63	0.70	1.09	0.59	0.70	0.75	0.81	0.62	1.03	1.00	0.53	0.75	0.99
Greece				-	0.95	1.08	0.82	0.58	0.85	0.38	0.58	0.81	1.02	1.15	1.06	0.95	0.76	0.79	1.14	0.69	1.08	1.15	1.37	1.23	0.67	1.31	1.11	1.15	1.19	1.28
Finland					-	0.82	0.63	0.86	0.93	1.11	0.74	0.71	0.32	1.07	1.26	0.68	0.57	1.11	0.76	0.79	1.28	0.61	0.84	0.94	1.20	1.21	1.41	1.29	1.28	0.94
France						-	0.74	0.74	0.41	0.82	0.62	1.06	0.63	1.15	0.52	0.78	0.36	0.81	0.69	0.97	0.84	0.62	1.19	0.95	0.77	1.22	1.16	0.85	1.18	1.19
Italy							-	0.54	0.65	0.78	0.60	0.85	0.84	0.81	0.65	0.86	0.55	0.66	0.82	0.81	0.58	0.73	0.74	0.60	0.46	1.02	0.87	0.60	0.69	1.04
Luxemburg								-	0.76	0.40	0.63	0.94	1.07	1.05	0.72	1.12	0.70	0.67	1.14	0.56	0.62	1.17	0.97	1.00	0.38	1.18	0.98	0.64	0.85	0.85
Netherland									-	0.74	0.63	0.67	0.94	0.78	0.63	0.79	0.62	0.50	0.70	0.88	0.89	0.63	1.39	0.95	0.61	1.22	1.21	0.93	1.20	1.30
Portugal										-	0.64	1.01	1.22	1.20	0.75	1.10	0.84	0.67	1.13	0.72	0.82	1.16	1.30	1.23	0.52	1.24	1.10	0.82	1.15	1.07
Sweden											-	0.63	0.61	1.15	0.62	0.55	0.40	1.04	0.72	1.18	1.06	0.49	1.27	0.83	0.81	1.06	1.01	1.15	1.14	1.21
UK												-	0.71	0.56	1.10	0.43	0.89	0.82	0.75	0.98	0.96	0.61	1.18	0.63	0.90	0.79	1.11	0.89	0.79	1.24
Canada													-	1.06	1.09	0.47	0.34	1.24	0.68	1.12	1.20	0.46	1.18	0.81	1.30	0.99	1.29	1.21	1.19	1.21
Norway														-	0.95	0.95	1.18	0.68	0.84	1.08	0.75	0.87	1.01	0.45	0.64	0.55	0.70	0.71	0.56	1.08
Japan															-	0.94	0.77	0.89	0.76	1.15	0.66	0.68	1.25	0.72	0.68	1.05	0.73	0.69	0.82	1.31
USA																-	0.63	1.18	0.58	1.00	1.18	0.38	1.33	0.75	1.26	0.94	1.25	1.18	1.17	1.25
Spain																	-	0.92	0.74	0.97	0.94	0.58	1.23	0.91	0.79	1.14	1.11	0.98	1.17	1.11
Denmark																		-	1.08	0.67	0.51	1.12	0.94	0.87	0.34	0.99	1.03	0.52	0.64	1.11
Ireland																			-	1.15	1.09	0.22	1.16	0.59	1.13	1.00	1.12	1.09	1.08	1.12
Cyprus																				-	0.90	1.19	0.95	1.28	0.93	1.31	1.47	0.99	1.25	0.97
Czech																					-	1.11	0.68	0.53	0.36	0.70	0.76	0.07	0.05	0.99
Hungary																						-	1.20	0.61	1.16	0.97	1.16	1.11	1.10	1.15
Latvia																							-	0.88	0.73	0.72	0.87	0.61	0.64	0.47
Poland																								-	0.72	0.50	0.71	0.55	0.33	1.14
Slovenia																									-	0.78	0.61	0.26	0.33	0.89
Turkey																										-	0.65	0.61	0.37	0.64
Romania																											-	0.65	0.49	0.83
Slovakia																												-	0.05	0.90
Estonia																													-	0.98
Lithuania																														-

Table A.4.: Distances based on comprehensive measure

	Austria	Belgium	Germany	Greece	Finland	France	Italy	Luxemburg	Netherland	Portugal	Sweden	UK	Canada	Norway	Japan	USA	Spain	Denmark	Ireland	Cyprus	Czech	Hungary	Latvia	Poland	Slovenia	Turkey	Romania	Slovakia	Estonia	Lithuania
Austria	-	0.44	0.27	0.68	0.67	0.34	0.48	0.66	0.41	0.81	0.31	0.76	0.57	0.91	0.58	0.64	0.32	0.48	0.53	0.81	0.86	0.30	1.05	0.58	0.44	0.98	1.16	0.82	0.86	0.39
Belgium		-	0.43	0.75	0.69	0.52	0.43	0.58	0.58	0.63	0.46	0.75	0.74	0.75	0.50	0.60	0.41	0.56	0.57	0.89	0.78	0.54	0.77	0.53	0.51	0.79	0.96	0.53	0.62	0.73
Germany			-	0.93	0.76	0.20	0.53	0.78	0.39	0.83	0.50	0.75	0.83	0.89	0.48	0.73	0.42	0.46	0.71	0.79	0.62	0.53	0.68	0.62	0.38	1.03	1.07	0.61	0.48	0.73
Greece				-	0.96	0.71	0.85	0.73	0.88	0.73	0.73	0.87	1.02	1.16	1.10	0.90	0.78	0.86	0.78	0.72	1.05	1.02	1.23	1.10	0.83	1.31	1.21	1.15	1.28	0.91
Finland					-	0.65	0.60	0.87	0.96	1.06	0.41	0.49	0.27	0.87	0.78	0.46	0.55	0.86	0.80	0.86	1.04	0.31	0.84	0.77	0.80	0.92	1.28	0.93	0.88	0.97
France						-	0.40	0.65	0.40	0.78	0.54	0.73	0.61	1.03	0.58	0.62	0.29	0.45	0.68	0.83	0.69	0.46	0.84	0.71	0.49	1.13	1.18	0.77	0.80	0.91
Italy							-	0.59	0.46	0.77	0.51	0.61	0.58	0.80	0.50	0.64	0.36	0.52	0.60	0.77	0.53	0.50	0.55	0.46	0.50	0.95	0.95	0.59	0.56	0.84
Luxemburg								-	0.77	0.69	0.77	0.80	0.76	0.88	0.65	0.86	0.66	0.72	0.94	0.75	0.70	0.89	0.80	0.61	0.70	1.14	1.08	0.78	0.69	1.14
Netherland									-	0.79	0.56	0.64	0.89	0.83	0.58	0.83	0.51	0.52	0.70	0.75	0.82	0.58	1.04	0.81	0.59	1.20	1.00	0.79	0.94	1.15
Portugal										-	0.88	1.09	1.15	1.04	0.85	1.10	0.88	0.88	0.89	0.76	0.90	1.15	1.02	1.06	0.89	1.05	1.00	0.79	1.14	1.08
Sweden											-	0.54	0.64	0.87	0.53	0.61	0.32	0.66	0.62	0.91	1.00	0.52	1.11	0.71	0.48	1.03	0.93	0.87	0.97	1.10
UK												-	0.37	0.70	0.74	0.36	0.76	0.74	0.70	0.95	0.97	0.47	1.10	0.44	0.69	1.02	1.04	0.92	0.78	1.16
Canada													-	0.99	0.56	0.22	0.53	0.90	0.67	1.03	0.97	0.32	1.08	0.50	0.91	0.94	1.14	1.02	0.88	1.26
Norway														-	0.95	0.92	1.02	0.73	0.89	0.93	0.77	0.90	0.83	0.60	0.78	0.65	0.88	0.79	0.64	1.11
Japan															-	0.56	0.60	0.83	0.75	1.10	0.70	0.59	1.03	0.42	0.73	0.81	0.64	0.84	0.66	1.17
USA																-	0.61	0.85	0.62	0.90	1.04	0.32	1.12	0.48	0.89	0.78	1.28	0.98	0.80	1.18
Spain																	-	0.50	0.69	0.78	0.79	0.45	0.84	0.67	0.46	1.05	1.16	0.92	0.80	1.07
Denmark																		-	0.87	0.58	0.57	0.75	0.70	0.59	0.29	1.08	0.97	0.62	0.55	0.97
Ireland																			-	1.02	0.88	0.49	0.95	0.75	0.90	0.89	1.07	0.85	1.05	1.01
Cyprus																				-	0.86	0.87	1.01	1.06	0.75	1.17	1.29	0.84	0.94	1.07
Czech																					-	0.88	0.37	0.49	0.50	0.83	0.91	0.32	0.20	0.88
Hungary																						-	1.02	0.58	0.75	0.92	1.07	0.90	0.74	1.09
Latvia																							-	0.73	0.73	0.80	0.97	0.52	0.46	0.63
Poland																								-	0.56	0.68	0.85	0.64	0.34	1.08
Slovenia																									-	1.00	0.76	0.47	0.50	0.82
Turkey																										-	0.90	0.80	0.58	0.84
Romania																											-	0.59	0.67	0.78
Slovakia																												-	0.18	0.54
Estonia																													-	0.65
Lithuania																														-

Table A.5.: Chronology of classical business cycles

(a) EMU-12 countries

	OE	BG	BD	GR	FN	FR	IT	IR	LX	NL	PT	ES
60's												
T									62.05		62.04	
P			66.03			64.04	64.01		65.02		66.04	
T			67.05			64.12	64.08		67.08		67.02	
70's												
P					70.07				70.01			
T					71.03				70.10			
P	74.06	74.06	73.08	74.02	74.07	74.07	74.06		74.08	74.08	74.03	74.08
T	75.10	75.04	75.07	74.07	75.09	75.05	75.04		75.08	75.08	75.08	75.04
P		76.11				76.09	77.01		76.05	76.09		
T		77.09				77.12	77.11		77.08	77.11		
P	79.12	79.12	79.12			79.07		79.09	79.12	79.11		79.08
T	81.07	80.12	82.11			81.04		80.12	81.04	82.11		82.08
80's												
P	82.01	82.04		80.04	81.07	81.12	80.03		82.02			
T	83.01	82.12		81.04	82.07	82.08	83.05		82.12			
P	86.03	85.11		82.05						84.06		
T	86.11	87.01		83.05						86.05		
P		89.07		85.12	89.07		89.12			87.01		89.07
T		91.08		87.06	91.06		91.04			88.04		91.03
90's												
P	91.08	92.01	92.02	89.04		91.12	91.09		90.06	92.01	90.08	91.12
T	93.06	93.11	93.07	93.01		93.08	93.07		93.08	93.06	93.10	93.04
P	95.06		94.12		95.01	95.03	95.12		95.08			95.05
T	96.02		95.10		95.11	95.12	96.12		96.05			96.01
P		98.07	98.07	99.08			97.10		98.02		99.06	
T		99.02	99.02	00.10			98.12		98.07		00.04	
00's												
P	00.11	00.11	01.02		00.12	00.12	00.12	01.02		00.12		00.11
T	01.09	01.09	01.11		01.12	01.12	01.11	01.07		-		01.12
P	02.04			02.04	02.06		02.07		02.06		02.07	
T	-			-	-		-		-		-	

(b) European and industrialized countries

	DK	SD	UK	CN	NW	JP	US	NBER
60's								
P			66.03	69.03	68.05	-	69.08	69.12
T			66.11	70.10	69.04	62.12	70.11	70.11
70's								
P		71.01	70.10		71.07			
T		71.09	72.02		72.03			
P	-	74.06	74.06	74.03	76.08	74.01	73.11	73.11
T	75.03	78.06	75.08	75.05	77.05	75.03	75.05	75.03
P	78.04							
T	79.01							
P	79.10	79.12	79.06	79.07				
T	80.11	82.11	81.05	80.06				
80's								
P				81.04	80.02	80.02	80.01	80.01
T				82.10	80.07	80.08	80.07	80.07
P					81.07	81.10	81.07	81.07
T					82.10	82.10	82.12	82.11
P	86.09	85.09	84.01	86.01		85.05		
T	87.10	86.04	84.08	86.08		86.08		
P	88.12						89.01	
T	89.08						89.07	
90's								
P	92.06	90.04	90.06	89.04		91.05	90.09	90.07
T	93.05	92.12	91.08	91.02		94.01	91.03	91.03
P				95.02				
T				95.12				
P	98.07		98.06		97.10	97.05		
T	98.12		99.02		99.04	98.08		
00's								
P		00.11	00.06	00.10	00.10	00.12	00.06	01.03
T		02.01	-	01.12	01.05	01.11	01.12	-
P	02.05				02.02			
T	-				-			

(c) Accession countries

	CY	CZ	ET	HN	LA	LI	PO	SK	SL	RO	TK
90's											
P	-	90.12		-			-			-	
T	91.02	91.09		91.12			91.11			92.07	
P	92.08	92.09			-			-	-		93.12
T	93.10	93.07			95.06			93.07	93.06		94.05
P	95.08				96.01	-					
T	96.12				96.12	96.06					
P		98.02	98.03		98.05	98.11	98.02	98.03	98.02	97.01	98.03
T		99.01	99.01		99.05	99.08	98.11	99.02	99.04	99.07	99.08
00's											
P	00.02			01.01			00.12				00.10
T	00.12			01.09			01.06				01.03
P	02.04								02.07		
T	-								-		

Table A.6.: Distances based on comprehensive measure. Supplementary information

	1990.01-2003.01				1961.01-1989.12		
Country	EMU-12	EU-15	Industrialized	Accession	EMU-12	EU-15	Industrialized
Austria	0.49	0.49	0.53	0.73	0.45	0.47	0.50
Belgium	0.54	0.55	0.57	0.69	0.46	0.49	0.50
Germany	0.53	0.54	0.58	0.68	0.45	0.47	0.48
Greece	0.80	0.80	0.85	1.07	0.70	0.73	0.72
Finland	0.77	0.73	0.69	0.86	0.64	0.66	0.66
France	0.49	0.50	0.54	0.79	0.46	0.50	0.52
Italy	0.54	0.54	0.56	0.65	0.55	0.58	0.58
Luxemburg	0.72	0.73	0.74	0.84	0.51	0.53	0.54
Netherlands	0.61	0.60	0.64	0.86	0.48	0.50	0.52
Portugal	0.80	0.83	0.88	0.98	0.73	0.74	0.76
Sweden	0.54	0.55	0.57	0.85	0.64	0.65	0.66
UK	0.74	0.73	0.68	0.85	0.66	0.67	0.70
Canada	0.70	0.68	0.66	0.88	0.52	0.55	0.53
Norway	0.92	0.89	0.90	0.80	0.96	0.95	0.95
Japan	0.65	0.66	0.66	0.77	0.50	0.54	0.55
USA	0.71	0.68	0.65	0.85	0.53	0.56	0.54
Spain	0.51	0.51	0.55	0.80	0.46	0.50	0.53
Denmark	0.63	0.64	0.68	0.69	0.72	0.74	0.75
Ireland	0.71	0.72	0.72	0.88	0.73	0.71	0.69
Cyprus	0.81	0.81	0.85	0.99	-	-	-
Czech Rep.	0.80	0.81	0.82	0.60	-	-	-
Hungary	0.58	0.58	0.56	0.87	-	-	-
Latvia	0.88	0.90	0.92	0.71	-	-	-
Poland	0.71	0.69	0.64	0.68	-	-	-
Slovenia	0.61	0.58	0.63	0.67	-	-	-
Turkey	1.04	1.04	0.98	0.86	-	-	-
Romania	1.09	1.07	1.05	0.89	-	-	-
Slovakia	0.79	0.79	0.81	0.56	-	-	-
Estonia	0.83	0.82	0.80	0.48	-	-	-
Lithuania	0.90	0.94	0.99	0.83	-	-	-

Table A.7.: Data sources

Series: Industrial Production index (s.a.)

Country	Code	Sample	Source
Austria	OE	1962.01-2002.12	OECD-MEI
Belgium	BG	1962.01-2003.01	OECD-MEI
Germany	BD	1962.01-2003.01	OECD-MEI
Greece	GR	1962.01-2003.01	OECD-MEI
Finland	FN	1962.01-2003.01	OECD-MEI
France	FR	1962.01-2003.01	OECD-MEI
Italy	IT	1962.01-2003.01	OECD-MEI
Luxemburg	LX	1962.01-2003.01	OECD-MEI
Netherlands	NL	1962.01-2003.01	OECD-MEI
Portugal	PT	1962.01-2003.01	OECD-MEI
Sweden	SD	1962.01-2003.01	OECD-MEI
UK	UK	1962.01-2003.01	OECD-MEI
Canada	CN	1962.01-2003.01	OCDE-MEI
Norway	NW	1962.01-2003.01	OCDE-MEI
Japan	JP	1962.01-2003.01	OCDE-MEI
USA	US	1962.01-2003.01	OCDE-MEI
Spain	ES	1965.01-2003.01	OECD-MEI
Denmark	DK	1974.01-2003.01	OECD-MEI
Ireland	IR	1975.07-2003.01	OECD-MEI
Cyprus	CY	1990.01-2003.01	IMF-IFS
Czech Rep.	CZ	1990.01-2003.01	OECD-MEI
Hungary	HN	1990.01-2003.01	OECD-MEI
Latvia	LA	1990.01-2003.01	OECD-MEI
Poland	PO	1990.01-2003.01	OECD-MEI
Slovenia	SL	1990.01-2003.01	OECD-MEI
Turkey	TK	1990.01-2003.01	OECD-MEI
Romania	RO	1990.05-2003.01	OECD-MEI
Slovakia	SK	1993.01-2003.01	IMF-IFS
Estonia	ET	1995.01-2003.01	OECD-MEI
Lithuania	LI	1996.01-2003.01	OECD-MEI

B. Appendix to Chapter 3

Figure B.1.: Business cycle characteristics: Duration

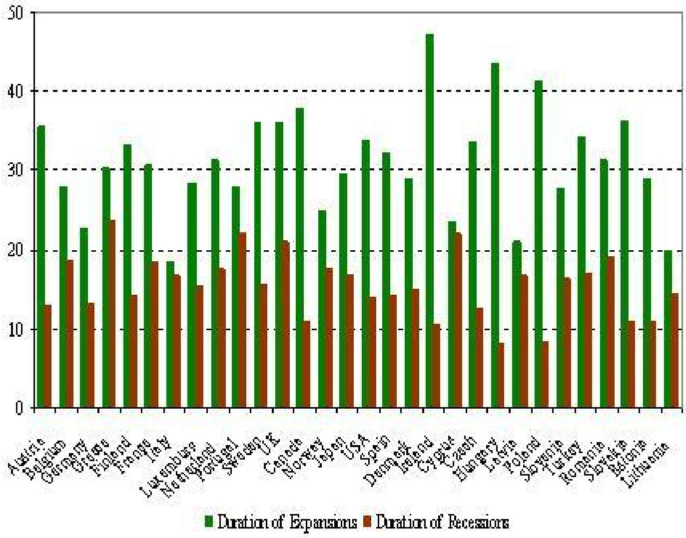


Figure B.2.: Business cycle characteristics: Amplitude

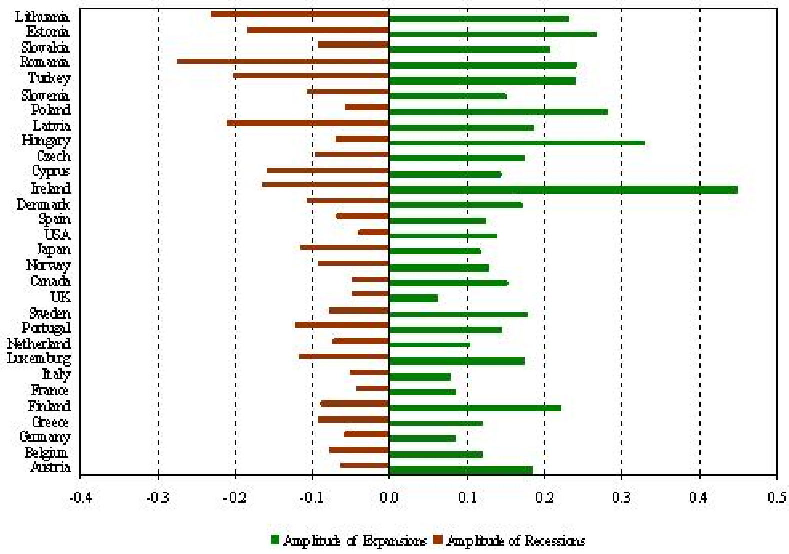
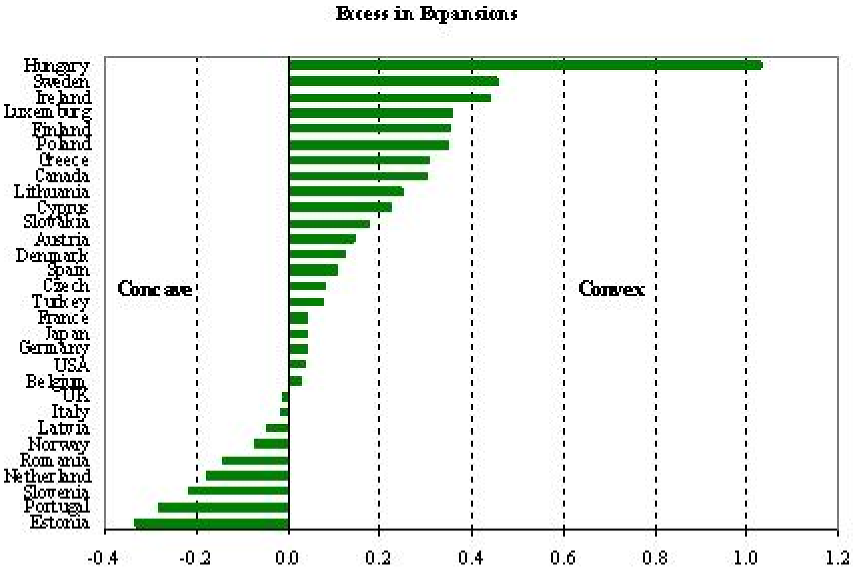
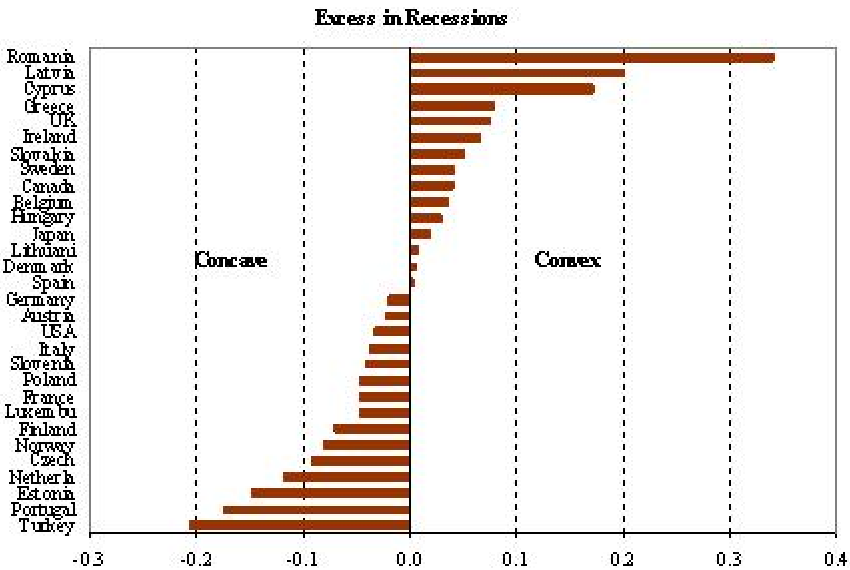


Figure B.3.: Business cycle characteristics: Excess



(a) Expansions



(b) Recessions

Table B.1.: Sensitivity analysis: duration (months)

	p = 0.95 E(l) = 19		p = 0.97 E(l) = 32		p = 0. 985 E(l) = 66	
Country	Expansions	Recessions	Expansions	Recessions	Expansions	Recessions
Austria	35.25	13.5	35.5	13	37	12.67
Belgium	27.25	18.75	28	18.75	28	18.6
Germany	24.5	14.6	22.75	13.17	21.8	12
Greece	28	22	30.33	23.67	32.33	25.25
Finland	33.75	14	33.33	14.25	32.5	14.33
France	29	18.25	30.67	18.5	32.5	18.75
Italy	19.4	17.25	18.5	16.67	17.5	16
Luxemburg	27.5	16.8	28.33	15.5	30	15
Netherlands	30.67	17.33	31.33	17.67	32.5	18
Portugal	27.33	21.75	28	22	30.5	21.75
Sweden	33.75	16.25	36	15.67	37.75	15
UK	34.67	19	36	21	36.33	24.33
Canada	37.75	11.33	38	11	40.33	11
Norway	26.25	17.5	25	17.6	23.8	18.2
Japan	27.75	17.25	29.75	16.67	30.5	16
USA	38.33	13.5	34	14	33.25	14.4
Spain	31.5	15	32.25	14.25	33.25	13.67
Denmark	29	14.75	29	15	28.67	17.33
Ireland	47	10.5	47.33	10.67	48	10.5
Cyprus	22.67	21.75	23.5	22	25	21.75
Czech Rep.	30.5	13	33.67	12.5	36	12
Hungary	43.33	8	43.67	8	43.67	8
Latvia	20.33	18.33	21	16.67	22.25	15.67
Poland	41.33	9	41.33	8.33	40.67	8
Slovenia	26.67	16.33	27.67	16.33	28.5	16
Turkey	32.75	17.6	34.33	17	35.33	17.33
Romania	30.33	18	31.33	19	32.67	19
Slovakia	34.67	11	36.33	11	37.33	11
Estonia	28	11	29	11	29.67	10.5
Lithuania	19.33	14.5	20	14.5	20.67	14.5
Average	30.62	15.59	31.2	15.51	31.94	15.55

Table B.2.: Sensitivity analysis: amplitude

	p = 0.95 E(l) = 19		p = 0.97 E(l) = 32		p = 0. 985 E(l) = 66	
Country	Expansions	Recessions	Expansions	Recessions	Expansions	Recessions
Austria	0.18	-0.17	0.18	-0.06	0.19	-0.06
Belgium	0.12	-0.09	0.12	-0.08	0.12	-0.07
Germany	0.09	-0.07	0.08	-0.06	0.08	-0.05
Greece	0.12	-0.09	0.12	-0.09	0.12	-0.09
Finland	0.22	-0.09	0.22	-0.09	0.22	-0.08
France	0.08	-0.04	0.08	-0.04	0.09	-0.04
Italy	0.08	-0.05	0.08	-0.05	0.08	-0.05
Luxemburg	0.18	-0.13	0.17	-0.12	0.17	-0.11
Netherlands	0.1	-0.08	0.1	-0.07	0.1	-0.07
Portugal	0.14	-0.12	0.14	-0.12	0.15	-0.12
Sweden	0.17	-0.08	0.18	-0.08	0.18	-0.07
UK	0.06	-0.05	0.06	-0.05	0.06	-0.05
Canada	0.15	-0.05	0.15	-0.05	0.16	-0.05
Norway	0.14	-0.1	0.13	-0.09	0.12	-0.09
Japan	0.11	-0.11	0.12	-0.11	0.12	-0.12
USA	0.14	-0.04	0.14	-0.04	0.14	-0.04
Spain	0.13	-0.07	0.12	-0.07	0.13	-0.07
Denmark	0.17	-0.11	0.17	-0.11	0.17	-0.1
Ireland	0.45	-0.17	0.45	-0.16	0.45	-0.17
Cyprus	0.15	-0.17	0.14	-0.16	0.14	-0.15
Czech Rep.	0.16	-0.1	0.17	-0.1	0.18	-0.1
Hungary	0.31	-0.07	0.33	-0.07	0.34	-0.07
Latvia	0.18	-0.25	0.18	-0.21	0.19	-0.19
Poland	0.28	-0.06	0.28	-0.06	0.28	-0.06
Slovenia	0.15	-0.11	0.15	-0.11	0.15	-0.1
Turkey	0.25	-0.21	0.24	-0.2	0.24	-0.2
Romania	0.23	-0.26	0.24	-0.27	0.24	-0.28
Slovakia	0.2	-0.09	0.21	-0.09	0.21	-0.09
Estonia	0.26	-0.18	0.27	-0.18	0.26	-0.18
Lithuania	0.24	-0.23	0.23	-0.23	0.23	-0.23
Average	0.18	-0.11	0.18	-0.11	0.18	-0.1

Table B.3.: Sensitivity analysis: excess

	p = 0.95 E(l) = 19		p = 0.97 E(l) = 32		p = 0. 985 E(l) = 66	
Country	Expansions	Recessions	Expansions	Recessions	Expansions	Recessions
Austria	0.1	-0.02	0.15	-0.02	0.18	-0.03
Belgium	0.02	0.02	0.03	0.04	0	0.06
Germany	0.04	-0.03	0.04	-0.02	0.04	-0.02
Greece	0.19	0.08	0.31	0.08	0.44	0.06
Finland	0.27	-0.07	0.35	-0.07	0.41	-0.05
France	0.04	-0.04	0.04	-0.05	0.06	-0.05
Italy	0	-0.04	-0.01	-0.04	-0.01	-0.04
Luxemburg	0.21	-0.07	0.36	-0.05	0.48	-0.04
Netherlands	-0.14	-0.1	-0.18	-0.12	-0.23	-0.14
Portugal	-0.18	-0.14	-0.28	-0.17	-0.42	-0.18
Sweden	0.37	0.02	0.45	0.04	0.5	0.06
UK	0.01	0.04	-0.01	0.07	-0.01	0.14
Canada	0.2	0.03	0.31	0.04	0.43	0.05
Norway	-0.13	-0.09	-0.07	-0.08	-0.07	-0.07
Japan	0.02	0.02	0.04	0.02	0.06	0.01
USA	0.03	-0.03	0.04	-0.03	0.03	-0.04
Spain	0.1	0	0.11	0	0.13	0.01
Denmark	0.1	-0.02	0.13	0.01	0.23	0.16
Ireland	0.54	0.06	0.44	0.07	0.16	0.06
Cyprus	0.2	0.16	0.22	0.17	0.25	0.15
Czech Rep.	0.11	-0.08	0.08	-0.09	0.13	-0.11
Hungary	0.73	0.03	1.03	0.03	1.29	0.03
Latvia	-0.04	0.27	-0.04	0.2	0.01	0.19
Poland	0.26	-0.05	0.35	-0.05	0.42	-0.05
Slovenia	-0.12	-0.03	-0.21	-0.04	-0.25	-0.06
Turkey	0.03	-0.23	0.08	-0.21	0.14	-0.22
Romania	-0.04	0.24	-0.14	0.34	-0.2	0.5
Slovakia	0.14	0.04	0.18	0.05	0.19	0.07
Estonia	-0.26	-0.14	-0.33	-0.15	-0.41	-0.15
Lithuania	0.16	-0.01	0.25	0.01	0.32	0.01
Average	0.1	-0.01	0.12	0	0.14	0.01

C. Appendix to Chapter 4

Table C.1.: Data sources

Series	Sample average	Source	Definition
Trade variable	1989-1998	IMF, Directions of trade	Nominal exports and imports
Savings ratio	1995	Penn World table	Current savings (% GDP)
Public balance	1998-2002	Eurostat	Net borrowing /lending of consolidated general government sector (%GDP)
Labour productivity	1995-1999	Eurostat	GDP in PPS per person employed relative to the EU-15 (EU15=100)
% Industrial production	1996-2000	World Dev. report	Percentage of industrial production over the total
% Agricultural production	1996-2000	World Dev. report	Percentage of agricultural production over the total
Inflation	1998-2000	Eurostat	Annual average rate of growth in the HICP
Geographical distances	2003	Eurostat	Distances between the capital cities in Km

Table C.2.: Some statistical descriptives

Variables	mean	std. dev.	min	max
distances (comprehensive)	0.78	0.21	0.24	1.33
diff. in trade intensity	0.04	0.07	0.0001	0.80
diff. in industrial production	0.07	0.05	0.0001	0.05
diff. in agricultural production	0.04	0.04	0.0001	0.19
diff. in labour productivity	0.38	0.27	0	1.12
diff. in saving ratio	0.09	0.07	0.0002	0.34
diff. in public balance	0.05	0.04	0.0002	0.25
diff. in inflation	1.67	1.39	0.003	6.13

Table C.3.: Business cycles distances and macroeconomic variables

Distances based on	Measure 1		Measure 2		Measure 3	
	OLS	IV	OLS	IV	OLS	IV
Constant	0.56 (0.06)	0.56 (0.04)	0.50 (0.03)	0.52 (0.04)	0.71 (0.03)	0.70 (0.04)
% Industry	1.21 (0.21)	1.22 (0.22)	0.70 (0.22)	0.66 (0.22)	0.54 (0.23)	0.54 (0.24)
% Agriculture	1.70 (0.30)	1.70 (0.30)	2.04 (0.31)	2.05 (0.31)	0.78 (0.33)	0.78 (0.33)
Saving ratio	0.37 (0.19)	0.37 (0.19)	0.42 (0.20)	0.39 (0.20)	0.35 (0.21)	0.35 (0.21)
Lab. productivity	0.05 (0.05)	0.05 (0.05)	0.001 (0.04)	-0.006 (0.05)	0.18 (0.06)	0.18 (0.06)
Public balance	0.62 (0.28)	0.63 (0.28)	0.95 (0.28)	0.90 (0.29)	-0.02 (0.30)	-0.01 (0.30)
Trade	-0.48 (0.16)	-0.46 (0.30)	-0.69 (0.16)	-0.93 (0.31)	-0.46 (0.17)	-0.41 (0.33)
R-squared	0.28		0.28		0.16	

D. Appendix to Chapter 5

D.1. Data sources

Table D.1.: Data sources

Variable	Code	Frequency	Sample	Source
Industrial production index (s.a.)	IPI	monthly	1959.01-2011.04	Federal Reserve Board (FRB)
Real personal income less transfer payments (s.a.)	INC	monthly	1959.01-2011.04	Bureau of Economic Analysis (BEA)
Non-farm payroll employees (s.a.)	EMP	monthly	1959.01-2011.04	Bureau of Labor Statistics (BLS) - CES Survey
Real manu-facturing and wholesale-retail trade sales	SALES	monthly	1959.01-2011.04	US Census department
Real gross domestic product (s.a.)	GDP	monthly	1947.Q1-2010.Q4	Bureau of Economic Analysis (BEA)

D.2. Modified Kalman filter for DFM with GARCH

Here we detail the steps of the extended Kalman filter to account for time-varying variances in the factor innovations following a GARCH model. First, the state-space representation of this model is:

$$y_t = \pi + Hf_t + \xi_t \tag{D.1}$$

$$f_t = Ff_t + u_t \tag{D.2}$$

$$Q_t = (1 - \alpha - \beta) + \alpha(u^2_{t-1|t-1} + P_{t-1|t-1}) + \beta Q_{t-1} \tag{D.3}$$

And the steps are:

1. Initialise $f_{0|0}$, $P_{0|0}$ and $Q_{0|0}$.
2. For $t = 1, 2, .., T$

    a) In the forecasting step the states and their variances together with the volatilities of the factor innovations (and idiosyncratic innovations, if we also consider this case) at time t are estimated using the information available until $t - 1$ with the next equations:

    $$f_{t|t-1} = Ff_{t-1|t-1} \tag{D.4}$$

    $$P_{t|t-1} = FP_{t-1|t-1}F' + Q_{t|t-1} \tag{D.5}$$

    $$Q_{t|t-1} = (1 - \alpha - \beta) + \alpha(u^2_{t-1|t-1} + P_{t-1|t-1}) + \beta Q_{t-1|t-1} \tag{D.6}$$

    Notice that the variance matrix of the states $P_{t-1|t-1}$is included in the second term in the right hand side of Equation D.6. Harvey et al. (1992) introduce this correction term, given that the factor is an unobserved component and must be estimated, to take the uncertainty in the factor estimates into account.

b) As soon as new data are available at time t, we compute the forecast errors and their corresponding variances,

$$v_t = y_t - \pi - Hf_{t|t-1} \tag{D.7}$$

$$\Sigma_t = HP_{t|t-1}H' + R \tag{D.8}$$

and update the estimates of the states together with their variances, and also the volatilities.

$$f_{t|t} = f_{t|t-1} + P_{t|t-1}H'\Sigma_t^{-1}v_t \tag{D.9}$$

$$P_{t|t} = P_{t|t-1} - P_{t|t-1}H'\Sigma_t^{-1}HP_{t|t-1} \tag{D.10}$$

$$Q_{t|t} = Q_{t|t-1} \tag{D.11}$$

The log-likelihood function is calculated as function of the forecast errors and their variances.

$$loglik_t = -0.5(\ln(2\pi) + \ln(|\Sigma_t|) + v_t'\Sigma_t^{-1}v_t) \tag{D.12}$$

D.3. Rao-Blackwellized Particle Filter (RBPF)

Rao-Blackwellized Particle Filter (RBPF) is an efficient sequential Monte Carlo (SMC) method because it recycles the simulated random variables by means of the popular Kalman filter algorithm. It is based on marginalisation and gaussian mixtures. In each iteration candidate values for the unknown variables (also called particles, because this methodology was developed in Physics) are generated. The name of Rao-Blackwellised is due to the Rao-Blackwellised theorem, which says that the expected value of any estimator conditioned on the information of a sufficient statistic is always better in terms of mean squared error than the estimator itself. In this case the proposed estimators given the information of the Kalman filter are better than the estimators themselves. Assuming that the values of all the parameters θ(i.e. loadings, autoregressive coefficients, variances) are known, the purpose of the filter is to generate particles from a posterior density (or filtering density) $P(f_t|I_t, \theta)$ using the likelihood $P(y_t|I_t, \theta)$ and the prior density (or forecasting density) $P(f_t|I_{t-1}, \theta)$ in the nex way:

$$P(f_t|I_t, \theta) \propto P(y_t|f_t, \theta)P(f_t|I_{t-1}, \theta) \tag{D.13}$$

The observation equation in the DFM provides information about the likelihood. And given that the DFM is conditionally linear and gaussian, the likelihood is also normal and can be written as a function of the forecast errors v_t and their variances Σ_t:

$$P(y_t|f_t, \theta) \sim N(v_t, \Sigma_t) \tag{D.14}$$

The state equation is useful to infer the prior distribution. Again, given that the model is conditionally linear and gaussian, this density will be normal with mean $Ff_{t-1|t-1}$ and variance $FP_{t-1|t-1}F' + Q_{t-1}$, this is, Equation D.4 and Equation D.5. So, the prior density is

$$P(f_t|I_{t-1}, \theta) = P(f_t|f_{t-1}, \theta) \sim N(Ff_{t-1|t-1}, FP_{t-1|t-1}F' + Q_{t-1}) \tag{D.15}$$

The posterior density is therefore approximated in this discrete way:

$$P(f_t|I_t, \theta) \simeq \sum_{j=1}^{D} w_t^{(j)} P(f_t|f_{t-1}^{(j)}, \theta) \tag{D.16}$$

where $w_t^{(j)}$are the importance weights which are a function of the likelihood function. Thus, the posterior density is approximated by a mixture of normals $P(f_1|f_{t-1}^{(j)}, \theta)$ with weights $w_t^{(j)}$. Due to that and the use of Kalman filter, this method is also known as *Mixture Kalman filter*.

Once the philosophy is clear, next we explain the steps of the algorithm.

1. Initialisation: At time 0 we generate D initial random particles for the states $\left\{f_{0|0}^{(j)}\right\}_{j=1}^{D}$. Their variances $\left\{P_{0|0}^{(j)}\right\}_{j=1}^{D}$, the volatilities of the factor innovations $\left\{Q_0^{(j)}\right\}_{j=1}^{D}$, and the importance weights $\left\{w_0^{(j)}\right\}_{j=1}^{D}$ are also initialised. Typically $f_{0|0}^{(j)}$ follows a standard normal, $P_{0|0}^{(j)}$ is the identity matrix, $Q_0^{(j)}$ is a random draw of a log-normal distribution and $w_0^{(j)} = 1/D$.
2. For $t = 1, 2, ..., T$
   a) Prediction step of the Kalman filter to get the state variables $\left\{f_{t|t-1}^{(j)}\right\}_{j=1}^{D}$ and their variances $\left\{P_{t|t-1}^{(j)}\right\}_{j=1}^{D}$. We also compute the forecast errors $\left\{v_t^{(j)}\right\}_{j=1}^{D}$ and their variances $\left\{\Sigma_t^{(j)}\right\}_{j=1}^{D}$, and the likelihood $\left\{lik_t^{(j)}\right\}_{j=1}^{D}$ given the observed y_t.

b) Compute the IMPORTANCE WEIGHTS for each particle from the likelihood function $\left\{\tilde{w}_t^{(j)}\right\}_{j=1}^{D}$ and normalize them $w_t^{(j)} = \tilde{w}_t^{(j)} / \sum_{j=1}^{D} \tilde{w}_t^{(j)}$. This normalization is important for the next step.

c) RESAMPLING of the particles: This step is necessary to reduce the sampling variability of the generated particles and to stabilise the algorithm. It consists in generating D values of a multinomial k which takes values $1, 2, ..., D$ with probabilities $w_t^{(j)}$, and select those particles for the states $\left\{f_{t-1|t-1}^{(k_j)}\right\}_{j=1}^{D}$and their variances $\left\{P_{t-1|t-1}^{(k_j)}\right\}_{j=1}^{D}$, and the volatilities of the factor innovations$\left\{Q_{t-1}^{(k_j)}\right\}_{j=1}^{D}$. In the literature some small modifications have been proposed in order to reduce the resampling variance or Monte Carlo variation such as the stratified resampling (for more details see Douc, Cappé and Moulines (2005)).

d) UPDATING step of the Kalman filter to get the filtered values of the state variables $\left\{f_{t|t}^{(j)}\right\}_{j=1}^{D}$ and their variances $\left\{P_{t|t}^{(j)}\right\}_{j=1}^{D}$. We also obtain the updated volatilities of the factor innovations $\left\{Q_t^{(j)}\right\}_{j=1}^{D}$ given that $\ln Q_t^{(j)} \sim N(\ln Q_{t-1}^{(j)}, \sigma_W^2)$ and the weights $w_t^{(j)} = 1/D$.

D.4. Parameter Kernel Smoothing (PKS)

Usually not only the state vector but the parameters are a priori unknown. This means that a new unkonwn term θ is included in the posterior density, in a way that it becomes a joint density of the state vector f_t and the parameters θgiven the information until time t, $P(f_t, \theta | I_t)$. Applying Bayes' theorem,

$$P(f_t, \theta | I_t) \propto P(y_t | f_t, \theta) P(f_t, \theta | I_{t-1}) \propto P(y_t | f_t, \theta) P(f_t | f_{t-1}, \theta) P(\theta | I_{t-1}) \quad \text{(D.17)}$$

the joint posterior density $P(f_t, \theta | I_t)$ is proportional to the likelihood $P(y_t | f_t, \theta)$, the conditional or forecasting density of the state variable given the parameters $P(f_t | f_{t-1}, \theta)$, and the density of the parameters given the information until $t-1$, $P(\theta | I_{t-1})$. Under the assumption of known parameters, the latter density is degenerate and we can skip that last term and in the joint distribution in Equation D.17. But more realistically if the parameters are unknown, the density of the parameters $P(\theta | I_{t-1})$ must be approximated to obtain draws from it. As already explained in section 4.2, one way of solving this issue is to treat the parameters as time varying, even though they are fixed, by adding small random disturbances to the parameters. Thus, the state vector is augmented with θ_t. But it is important to clarify that θ_t means that our estimation about the values of the parameters changes with the information available. However, the parameters are actually fixed. Typically the following parameter learning evolution is imposed over the D draws

$$\theta_t^{(j)} = \theta_{t-1}^{(j)} + \zeta_t^{(j)} \tag{D.18}$$

with $\zeta_t^{(j)} \sim N(0, W_t^{(j)})$ for $j = 1, 2, .., D$ and $t = 1, 2, ..., T$.

This artificial evolution could lead to very diffuse values for the draws of the parameters, and hence, cause problems of precision or loss of information. For this reason, West (1993) proposed to smooth these draws using kernel smoothing methods. In this way, we get draws of θ at time t given the information until $t-1$ by means of the next discrete Monte Carlo approximation as a weighted mixture of normals

$$P(\theta_t|I_{t-1}) \approx \sum_{j=1}^{D} w_{t-1}^{(j)} N(\theta_t|m_{t-1}^{(j)}, h^2 V_{t-1}) \tag{D.19}$$

where $N(\bullet|m_{t-1}, h^2 V_{t-1})$ is a multivariate normal density (i.e. Gaussian kernel) with mean m_{t-1} (i.e. kernel location) and variance $h^2 V_{t-1}$, and $w_{t-1}^{(j)}$ are the importance weights. Notice that h is a smoothing parameter, strictly positive, and $V_t = \sum_{j=1}^{D} (\theta_{t-1}^{(j)} - \bar{\theta}_{t-1})^2 / D$ is the Monte Carlo posterior variance and represents the kernel rotation and scaling. Furthermore, the next shrinkage rule for the mean $m_{t-1}^{(j)}$ is going to push draws of $\theta_t^{(j)}$towards the Monte Carlo finite mean $\bar{\theta}_{t-1} = \sum_{j=1}^{D} \theta_{t-1}^{(j)} / D$ and avoid over-dispersion

$$m_{t-1}^{(i)} = a\theta_{t-1}^{(j)} + (1-a)\bar{\theta}_{t-1} \tag{D.20}$$

with the number a specified as function of a discount factor $\delta \in (0, 1]$, this is, $a = (3\delta - 1)/2\delta$. In practice a typically takes values between 0.95 and 0.99. The smoothing parameter h depends on a, usually specified in this way $h = \sqrt{(1 - a^2)}$. It is important to mention that when dealing with variances and parameters restricted to a finite range such as the autoregressive coefficients is necessary to transform them with the logarithm in the first case or the logit transformation in the latter to use a normal approximation implied in Equation D.18.

D.5. General Algorithm

Finally, plugging together RBPF and PKS these are the steps of the general algorithm:

1. INITIALISATION step to get D draws from:
   a) the parameters $\theta_0^{(j)} \sim p(\theta_0)$ for $j = 1, 2, .., D$.
   b) the states $\left\{f_{0|0}^{(j)}\right\}_{j=1}^{D}$ and their variances $\left\{P_{0|0}^{(j)}\right\}_{j=1}^{D}$, and the volatilities of the factor innovations $\left\{Q_0^{(j)}\right\}_{j=1}^{D}$.
   c) the importance weights $w_0^{(j)} = 1/D$ for $j = 1, 2, ..., D$.
2. For t=1,2,..,T
   a) Compute the mean $m_{t-1}^{(j)}$ using Equation D.20 and the variance V_{t-1} of the draws $\theta_{t-1}^{(j)}$.
   b) PREDICTION step of the Kalman filter to get the predicted states $\left\{f_{t|t-1}^{(j)}\right\}_{j=1}^{D}$ and their variances $\left\{P_{t|t-1}^{(j)}\right\}_{j=1}^{D}$. We also compute the forecast errors $\left\{v_t^{(j)}\right\}_{j=1}^{D}$ and their variances $\left\{\Sigma_t^{(j)}\right\}_{j=1}^{D}$, and the likelihood $\left\{lik_t^{(j)}\right\}_{j=1}^{D}$ given the observed y_t.
   c) Compute the IMPORTANCE WEIGHTS for each particle from the likelihood function $\left\{\tilde{w}_t^{(j)}\right\}_{j=1}^{D}$ and normalize them $w_t^{(j)} = \tilde{w}_t^{(j)} / \sum_{j=1}^{D} \tilde{w}_t^{(j)}$.
   d) RESAMPLING of the particles using draws from a multinomial k that can take values $1, 2, ..., D$ with probabilities $w_t^{(j)}$, and selecting these particles for the states $\left\{f_{t-1|t-1}^{(k_j)}\right\}_{j=1}^{D}$ and their variances $\left\{P_{t-1|t-1}^{(k_j)}\right\}_{j=1}^{D}$, and the volatilities of the factor innovation $\left\{Q_{t-1}^{(k_j)}\right\}_{j=1}^{D}$.
   e) UPDATING step for:
      i. the parameters $\theta_t^{(j)} \sim N(m_{t-1}^{(k_j)}, h^2 V_{t-1})$.
      ii. the state vector $\left\{f_{t|t}^{(j)}\right\}_{j=1}^{D}$ and its variance $\left\{P_{t|t}^{(j)}\right\}_{j=1}^{D}$ using the Kalman filter and the selected particles from the previous step.
      iii. the volatilities of the factor innovations $\left\{Q_t^{(j)}\right\}_{j=1}^{D}$ considering that $\ln Q_t^{(j)} \sim N(\ln Q_{t-1}^{(j)}, \sigma_W^2)$.
      iv. the importance weights $w_t^{(j)} = 1/D$ for $j = 1, 2, ..., D$.

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Dissemination of this doctoral thesis

Most of the contents of Chapters 2 and 3 and part of Chapter 4 are already published in two articles jointly with Máximo Camacho and Gabriel Pérez-Quirós.

Article 1: “Are European Business cycles close enough to be just one?”, *Journal of Economic Dynamics and Control* 30, pp. 1687-1706 (2006). According to Google scholar, this article has so far received 117 citations. Apart from that, this work was presented in different seminars and conferences such as at the European Commission, the European Central Bank, the Banco de España, MadMac (Madrid Macroeconomics), the 10th Annual conference on computing in economics and finance, the EABCN workshop on business cycles and acceding countries, VIII Encuentro de Economía Aplicada, and the 7th INFER Workshop on Economic Policy: The consequences of EU Enlargement to Eastern European Countries among others. It was also awarded with the prize “ALdE (Asociación Libre de Economía) jóvenes investigadores” in 2005.

Article 2: “Do European Business Cycles look like one?”, *Journal of Economic Dynamics and Control* 32, pp. 2165-2190 (2008). This article has been cited 36 times since it was published according to Google scholar. This work was also presented in the Banco de España, the 12th International Conference on Computing in Economics and Finance, the 8th CEPR/ESI annual Conference, and the 9th World Congress of the Econometrics Society.

The Journal of Economic Dynamics and Control has an Impact Factor of 1.117 in 2010 and a 5-year Impact Factor of 1.303 in the Journal of Citation Reports (JCR).