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Is Decoupling in action?

Antonio Pesce^{*}

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Abstract

Emerging market economies (also known as emerging economies, EEs) have become important on the world economic stage, where they now play a vital role in international trade and financial flows and account for a conspicuous fraction of the global economic dynamic. Despite the relatively tepid economic growth of advanced economies (AEs) from 2004 to 2007, the growth of EEs continued to be strong during that same period. This behaviour provided some evidence for the so-called “decoupling hypothesis” that EEs have, over time, become less dependent on AEs. With the recent global financial crisis, the direction of the debate on the “decoupling” has been partially changed; thus, the discussion remains unresolved. The decoupling hypothesis implies two main consequences. First, the comovement of economic cycles between AEs and EEs should decrease over time. Second, the resilience of the EEs to adverse scenarios in AEs should increase through time. This work sought to identify empirical evidences of the two consequences of decoupling. Two approaches were employed: 1) the Euclidean distance was used to evaluate the correlation of the international economic cycles, and 2) a time-varying Panel VAR model was used to decompose fluctuations in GDP into global, regional, group and country specific components and quantify the time path of the resilience of EEs. Although the Euclidean distance does not provide a clear indication in favour of decoupling, if we consider a sufficiently lengthy time period what does emerge, albeit subject to certain geographical differences, is that the connection between EEs and EAs has changed in that EEs are more resilient to the adverse scenarios that may arise in AEs. This result lends support to the decoupling hypothesis, although it is also clear that the process of strengthening of the EEs, that is, the decoupling process, has not emerged in a gradual, progressive manner, but has, on the contrary, followed a more complex dynamic characterised by “alternate phases”. This discontinuity over time, together with the geographical peculiarities of the phenomenon, is still to be fully understood.

JEL classification: C11, C33, E32, F44

Keywords: Economic Cycles, Emerging and Advanced Countries, Bayesian methods

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1. Introduction

Emerging market economies (EEs), have become important on the world economic stage, where they now account for a conspicuous share of the global economic growth and their importance is increasing in various other economic dimensions, such as foreign direct investment and portfolio investment flows.

With this growing importance of EEs, an increasing number of papers have attempted to assess the empirical features of EE dynamics and, since 2006-2007, economists have fiercely debated whether the national economic cycles are converging or whether the cycles of EEs and advanced economies (AEs) are becoming disconnected, with EEs becoming more resilient to shocks in AEs (the so-called “decoupling hypothesis”). The convergence argument is linked to the idea that all economies have become more intertwined through trade and finance, which should make the national economic cycles more synchronised. In contrast, the decoupling argument is linked to the issue of the recent and prominent development of real and financial linkages among EEs¹. These two opposing perspectives reflect the fact that theoretical models often make different predictions about the effects of trade and financial integration on the interrelationships among national economic cycles.

Trade theories imply that an increase in trade linkages leads to an increase in intra- or inter-industry product specialization². The way in which the increased specialization affects the degree of comovement in national economic cycles is thought to depend on the nature of specialization (Frankel and Rose 1998). More precisely, if the industry shocks are important in driving economic cycles, then the comovement of economic cycles is expected to decrease when stronger trade linkages are associated with interindustry specialization, whereas the comovement is expected to increase when stronger trade linkages are associated with intraindustry specialization. The two types of industrial specialization are not mutually exclusive: comparative advantages encourage interindustry specialization, and scale economies sustain intraindustry specialization (Krugman, 1981). Thus, in theory, the effect of the production specialization on the degree of comovement and linkages in economic cycles is not univocal but depends on which type of production specialization prevails.

There is not univocal theoretical predictions about the effects of financial integration on the linkages of national economic cycles. As explained in depth by Kose and Prasad (2010), financial integration could decrease the synchronicity of economic cycles, stimulating interindustry production specialization through the reallocation of capital and the comparative advantage of countries. On the other side, contagion effects, transmitted through financial linkages, could increase synchronicity via cross-country spillovers of macroeconomic

1 These linkages can be observed in, for example, the recently increased trade among emerging countries, which currently accounts for over half of the total exports of emerging markets; source: International Monetary Fund (IMF), World Economic Outlook (WEO), April 2012.

2 Interindustry trade is the exchange of totally different products between countries. Intraindustry trade is the two-way trade of products in the same industry classification. See Krugman (1981) for more details.

fluctuations. The comovement of economic cycles could also be increased through demand-side effects, as long as the financial integration determines a similar dynamic of wealth across countries.

Given that the effects of trade and financial integration on the interrelation of national economic cycles are theoretically predicted to be non-univocal, an empirical analysis could help to gain insight into this topic. As stated by Kose and Prasad in reference to the relationship between the economic cycles of EEs and AEs, “*There is a need for more formal empirical analyses...*” (pg. 173, Kose and Prasad, 2010). However, the uncertainty regarding the phenomenon of decoupling, that exists in the economic theory, is also present in the results of empirical literature.

The decoupling hypothesis essentially refers to a structural change in the degree of business cycle interdependence between the two groups of economies (EEs and AEs) and it implies two consequences that should be empirically observable: 1) a decreasing comovement of economic cycles between AEs and EEs over time, 2) an increasing resilience of the EEs to adverse scenarios in AEs.

The first point has been discussed and presented in the most recent economic literature with empirical research on a large set of advanced and emerging countries belonging to different geographical regions, see Kose (2012) and Wälti (2012). Kose et al. (2012)³, similar to Kose et al. (2003), perform their investigation on a dataset of 106 countries, employing a dynamic factor model⁴ to decompose the national economic cycles of each country into different components⁵. Through variance decomposition analysis, they conclude that the global factor became less important for macroeconomic fluctuations in AEs and EEs during the period of globalization (from the 1980s), whereas the group-specific factor became significantly more important for both AEs and EEs. This result shows a disconnection between the economic cycles of EEs and AEs that, in the authors’ opinion, supports the decoupling hypothesis. Wälti (2012), in his study of the economic cycles⁶ of 30 emerging and 26 advanced markets, concludes that there is not evidence in favour of the decoupling. Rather, the interdependence of the economic cycles appears to have become stronger over time, as the correlation between the economic cycles in emerging and advanced markets has shown an increasing path. He also finds no evidence of a structural change in the coefficient of the economic cycle of AEs as regressors of the equations that he used to estimate the economic cycles of EEs⁷.

3 An earlier version of this article was published by the same authors in NBER Working Paper 14292, 2008.

4 See Kose et al. (2003) for details on this approach.

5 Components include the global factor, representing the economic dynamic common to all countries; group factors, representing the economic dynamics common to the EEs, developing economies (DEs), and AEs, respectively; and country-specific factors, representing the specific economic dynamic of each national economic cycle.

6 Wälti (2012) performs his analysis on the so-called deviation cycle, which is the difference between the actual GDP and its trend.

7 Following Levy-Yeyati (2009), Wälti performs many regressions. In each estimation, he regresses the pooled economic cycles of EEs on the economic cycles of AEs, as well as a dummy variable that, in each regression, takes a value of 1 from a different chosen year (between 1999 and 2007) until the last year of the sample, namely 2008, to capture changes in the coefficient of the economic cycles of AEs.

About the second point, to the best of my knowledge, there are not contributions that quantify in a global context how the response of EEs to adverse scenarios in AEs has changed through time.

The purpose of the present research is to extend the empirical research on the decoupling phenomenon by measuring how the resilience of EEs has changed over time, defining the main components of the national economic cycle, and also measuring the correlation among the national economic cycles.

To this end, two recently developed econometric tools: the Euclidean distance proposed by Wälti (2012) and the time-varying Panel VAR model with factorization of the coefficients⁸, as proposed by Canova and Ciccarelli (2009)⁹, were used to study a sample of 112 countries (of which 23 advanced countries, 59 emerging countries and 30 developing countries). The Euclidean distance between two standardized series conveys the same qualitative information as the correlation coefficient, however the Euclidean distance has the considerable advantage that it can be computed on an annual basis, unlike the correlation coefficient that must be estimated over relatively large subsamples of data; consequently, the Euclidean distance may be used to better evaluate the changes in the correlation over time also at the end of the sample period.

The model proposed by Canova and Ciccarelli (2009) has various advantages. First, the use of the factorization of the coefficients offers a great advantage from the computational perspective and also from the economic point of view. From the computational perspective, it significantly reduces the number of parameters that must be estimated. This is very important in managing large dynamic panel, as the case of this paper. From the economic perspective, the factorization of coefficients, as explained in deep by Canova and Ciccarelli (2009), produces indices that can be interpreted as components of the national economic cycles, e.g. global, regional, and country-specific cycle components. Second, The model specification is well suited for investigating how the international transmission of shocks from AEs to EEs is changed over time as the model can account for cross-unit lagged interdependencies. Dynamic feedbacks across countries are possible and this aspect increases the realism of the experiment in terms of evaluating the response of EEs to adverse scenarios in AEs in a global framework. Moreover, instead of implementing a structural break in the model coefficients, they are allowed to vary over time. The time variations of coefficients should be the solution more appropriate to study the decoupling that, presumably, is more similar to a gradually evolving phenomenon, rather than a structural break that occurs at a given instant in time.

⁸ Coefficients of the model depend on a low-dimensional vector of time-varying factors, which can capture coefficient variations that are common across countries ("global" effect); variations that are specific to a group to which the country belongs, namely, advanced or emerging groups ("group" effect); variations that are specific to each geographical region ("region" effect) and to a specific country ("country" effect); or variations that are specific to the variable ("variable" effect).

⁹ Canova Ciccarelli (2009) changes the model proposed in Canova and Ciccarelli (2004) by providing a coefficient factorization that facilitates the estimation process.

The empirical investigation was performed in two steps. In the first step, the correlation of economic cycles between AEs and EEs was evaluated.

In the second step I used the above explained time varying VAR model. Three different model specifications were implemented, which differed in terms of their coefficients factorization (i.e., factors). The first model specification included the global factor (i.e., the factor that was common to all countries) and the country-specific factors. The second model specification added the group factors (i.e., the EEs, the developing economies [DEs], and the AEs factors) to the global and country-specific factors. The third model specification added the regional factors (i.e., factors that were common among countries in the same geographical region, e.g., North and Central America, Latin America, Europe, Asia, Middle East and North Africa [MENA], Sub-Saharan Africa [SSA], Oceania, etc.) to the global and the country-specific factors. According to the estimated marginal likelihood, the model specification with the regional factors combined with the global and the country-specific factors was preferable to the other two models. This model was used to perform counterfactual analyses (CAs) to measure the impact on EEs of simulated shocks spreading from AEs. The intensity of the impact suggests the degree of resilience of the EEs to shocks from EAs, so it can be used as an indicator of EEs' resilience. The CA experiments were conducted for different years of the sample period, and the results were compared across time to determine whether EEs show a tendency to become more or less resilient to adverse scenarios in AEs, in other words, to determine whether the intensity of the impact shows a tendency to weaken or to become stronger over the sample period.

In terms of the principal results, two points may be made here. Firstly, a graphical inspection of the Euclidean distance indicator suggests that the synchronicity between the economic cycles of EEs and AEs increased, rather than decreased, from the latter half of the 1970s to the early 2000s, even though signs of a possible inversion in this trend appeared during the latter half of the 2000s. An analysis of the Euclidean distance fails to provide any clear, prevalent evidence in favour of the decoupling hypothesis. Nevertheless, this could be distorted by the fact that the degree of correlation between EEs and EAs may vary not only as a result of a change in the economic ties between the countries in question, which may become weaker or stronger, but also in virtue of a change in the nature of the shocks, which may become more or less global. Secondly, contrary to the Euclidean distance indicator, the counterfactual analyses supports the decoupling hypothesis as they have shown that the resilience of EEs to shocks spreading from AEs has increased over the course of thirty years, even though the process has not been a gradual, constant one, but indeed has been characterised by an alternation of periods of greater resilience and periods of lesser resilience. In particular, over the last fifteen years, EEs have lost some of their resilience to external shocks, but notwithstanding this, their degree of resilience remains higher now than it was during the early 1980s.

The rest of the paper is organized as follows. The next section discusses the international synchronicity of economic cycles through the Euclidean distance method. Section 3 presents the empirical model and the results of the CA experiments. Section 4 concludes the paper.

2. Synchronicity of international economic cycles

The decoupling hypothesis is the idea that business cycles in emerging market economies have become more independent from business cycles in advanced economies. As explained in the Section 1, this idea implies two consequences: 1) the comovement (synchronicity) of the economic cycles of EEs and AEs should show a decreasing path, and 2) the resilience of EEs to adverse scenarios in AEs should show an increasing trend over time. The aim of this section is to investigate the first consequence: namely, the international synchronicity of economic cycles.

2.1 Method

Economic cycle synchronicity is usually measured as the correlation between economic cycles see, e.g., Frankel and Rose (1998), Rose and Engel (2002), Kose et al. (2003), Imbs (2004, 2006), Baxter and Kouparitsas (2005), and Fidrmuc and Korhonen (2006). Correlation coefficients are estimated over (typically rolling) subsamples of data e.g., Flood and Rose (2009). However, the last-estimated correlation coefficient may not identify the change in the degree of the economic cycle interdependence when this change occurs around the end of the time window used to estimate the correlation coefficient. For this reason, in the present paper, the economic cycle synchronicity was evaluated by using the measure proposed by Wälti (2012): namely, the Euclidean distance between two standardized variables.

The Euclidean distance¹⁰ is the absolute value of the numerical difference between two time series at each time t . When the difference is zero at time t , the two variables are perfectly in tune at that time. Any positive value indicates imperfect synchronisation; the larger the distance between economic cycles is, the less interdependent they are. Although this measure conveys the same qualitative information as the correlation coefficient, it can be computed for each year and allows for the proper evaluation of the synchronicity of the time series at the end of the sample period. Euclidean distances were computed to measure the economic cycle synchronicity of emerging and developing economies (different groups were considered: all EEs; EEs and DEs together; Latin American, Asian, European, MENA, and SSA emerging

¹⁰ See the article of Wälti for details on the Euclidean method.

economies) with the group of all advanced economies¹¹. The measure of the economic cycle interdependence for each group was the average of the Euclidean distance of the group members¹².

Some authors, such as Kose et al. (2012), focus on the growth rate of the real GDP as a measure of the economic cycle. However, as was recently outlined by Reinhart and Rogoff (2012), the impact of population growth on GDP growth is an important consideration when working with historical series. The GDP growth can be misleading when the population growth rate changes significantly, as is the case in many EEs. Therefore, in this paper, the real gross domestic product per head at purchasing power parity (from now on simply GDP) was used, with data from 1970 to 2010 taken from the Penn World Table 7.1¹³. The economic cycle was considered to be the growth rate cycle; thus, the economic cycle was computed as the annual growth rate of the GDP. To evaluate the synchronicity through the Euclidean distances, each growth rate cycle was standardized by subtracting its mean and dividing by its standard deviation (Wälti, 2012).

2.2 Results

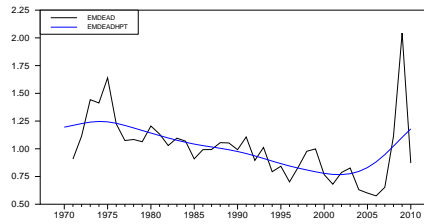
Figure 1 shows the degree of economic cycle synchronicity of the group of all EEs plus all DEs with the group of all AEs (panel 1) and the degree of economic cycle synchronicity of EEs with AEs (panel 2). Since the second half of the 1970s, the synchronicity has been increased (i.e., the Euclidean distance has been decreased), and it reached a record high in 2006 (i.e., the record low for Euclidean distance). With the escalation of the worst financial crisis of the last 40 years which, with different degrees of impact, spread from the USA to many other countries in the world, the indicator jumped to historic highs in 2009, indicating a low degree of correlation between the economic cycles of advanced markets and emerging markets. This result was temporary and by early 2010 the indicator returned to just under the average of the last 20 years¹⁴.

11 See Appendix A for the list of all countries and their grouping into EEs, DEs, and AEs. According to Pritchett (2000), AEs were defined primarily by their pre-1990 membership in the Organization for Economic Cooperation and Development. All other economies were classified as EEs or DEs. The DEs were defined based on their current eligibility for concessional IMF loans. Remaining countries were classified as EEs. As a result of this classification scheme, some economies currently classified as AEs by the WEO (2012) of the IMF were classified as EEs in this article. According to Abdul Abiad et al. (2012), this categorization is appropriate because it is acceptable to think that those countries have acted more like EEs than AEs over the past 40 years.

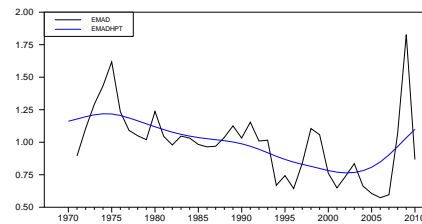
12 The unweighted average was chosen because the data were “per head” and, thus, already weighted by the dimension of the country.

13 Alan Heston, Robert Summers, and Bettina Aten, Penn World Table Version 7.1, Center for International Comparisons of Production, Income, and Prices at the University of Pennsylvania, Nov. 2012.

14 Wälti (2012) previously applied this same approach to the GDP deviation cycles of 56 countries, covering the period from 1980 to 2008. Despite the different sets of countries and data, Wälti came to the same conclusions as presented above. However, due to the lower temporal extension of his sample, he was unable to observe the temporary jump of the indicator in 2009.



1 EEs plus DEs vs. AEs



2 EEs vs. AEs

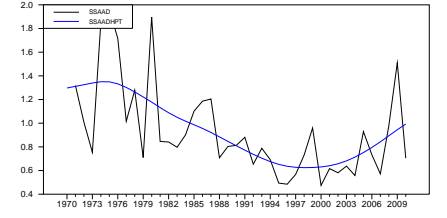
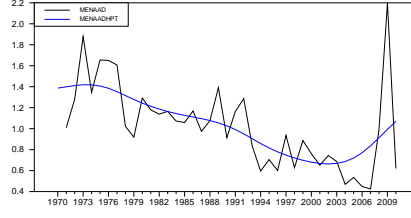
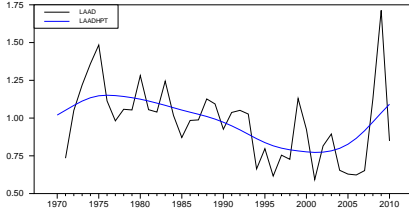
Figure. 1 Euclidean distance: EEs plus DEs vs. AEs and EEs vs. AEs

To check if the above results were general and reflected similar figures in subsamples of EEs grouped by geographical area, the synchronicity of economic cycles of five EE subgroups (Latin American, MENA, SSA, Asian, and European EEs) with all AEs was plotted in Figure 2. The pattern of the subgroups¹⁵ was substantially consistent with the correlation shown in the Figure 1, although some regional peculiarities emerged. For the Latin American, MENA, and SSA EEs, the degree of synchronicity with the AEs was very markedly increased (Figure 2, panel 1 to 3), whereas the synchronicity showed a more gradual path for the emerging Asian countries (Figure 2, panel 4) and an almost-flat path for the European emerging countries (Figure 2, panel 5)¹⁶.

In general, the correlation between the economic cycles of EEs and AEs increased from the latter half of the 1970s up to the early 2000s, and it was only during the latter half of the 2000s that possible signs of an inversion in this trend emerged (see the Hodrick-Prescott filter, indicated by the blue lines in the Figures). These results suggest that insofar as the degree of correlation between EEs and AEs may be determined by the decoupling phenomenon, there is no clear, prevalent evidence of decoupling. Unfortunately, however, we cannot know whether the reduction or increase in the correlation is due to the fact that over the course of time, EEs and EAs have become interlinked to a greater or lesser extent, or whether it is due to a change in the nature of economic shocks becoming more or less global than before. Regardless of the fundamental economic ties linking the various countries, it could be that during a period characterized by global shocks, the correlation among economic cycles is greater than it is in a period characterized by local shocks, as a global shock acts by rendering the economic cycles of different countries more similar. Therefore, for the purposes of our investigation into the decoupling phenomenon, the interpretation offered by the Euclidean distance, namely the correlation, is not so simple since it is difficult to distinguish between the effect due to the historical evolution of the actual economic ties among countries and the effect due to the historical evolution in the nature of the shocks. The Euclidean distance, although useful, can only provide certain rough indications.

¹⁵ The results of each single EE are available on request to the author.

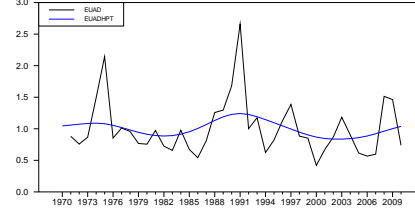
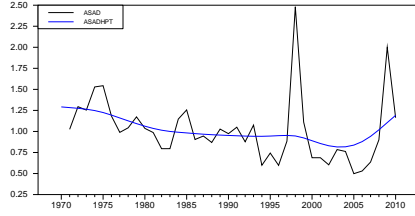
¹⁶ The same pictures as are shown for Figures 1 and 2 were obtained when the deviation cycle, instead of the growth cycle, was used. See Appendix B for these results.



1. Latin America EEs vs. AEs

2. MENA EEs vs. AEs

3. SSA EEs vs. AEs



4. Asia EEs vs. AEs

5. Europe EEs vs. AEs

Fig. 2 Euclidean distance: EEs regional groups vs. all AEs

For the purposes of this paper, it is important to conduct an analysis enabling us directly to observe the influence of the EAs on the EEs, and how this influence has changed over the course of time. We have tried to do so by means of the simulation experiments presented in the following section.

3. Responses of EEs to adverse scenarios in AEs: have they changed over time?

In this Section a time-varying Panel VAR model of the type developed in Canova and Ciccirelli (2009) and Canova et al. (2007) was applied to decompose GDP¹⁷ fluctuations into global, regional, group and country specific components and to quantify how the responses of EEs to adverse scenarios in AEs have changed over time.

3.1 Model

The empirical model employed has the following form

$$y_{it} = \sum_{L=1}^p d_{it,L} Y_{t-L} + c_i + e_{it}$$

where $i = 1, \dots, N$ are countries; $t = 1, \dots, T$ is time; p is the number of lags; y_{it} is a scalar, namely, the GDP growth rate of each country i at time t ; $Y_t = (y_{1t}, \dots, y_{Nt})'$ is a column vector with dimension N ; $d_{it,L}$ are row vectors of dimension N for $L = 1, \dots, p$; c_i is a constant term for each country i at time t ; and e_{it} is the disturbance for the country i at time t .

The system of equations can be written as:

¹⁷ As in the Section 2, data are standardized.

$$Y_t = \sum_{L=1}^p D_{t,L} Y_{t-L} + C + E_t, \quad E_t \sim N_N(0, \Omega) \quad (1)$$

where $D_{t,L}$ is an $N \times N$ matrix in which the i -th row is the vector $d_{it,L}$; $C = (c_1, \dots, c_N)'$; and E_t is a vector of random disturbances $E_t = (e_{1t}, \dots, e_{Nt})'$, for which a normal distribution is assumed.

The system of equations (1) displays some unique features that add realism to the empirical model and make it ideal for the purposes of this article. First, the coefficients are allowed to vary over time. As described in Section 1, time variations are really appropriate to examine the evolution of the economic cycles and to study the decoupling phenomenon. Second, whenever the $N \times N$ matrix $D_{t,L}$ is not diagonal for some L , cross-unit lagged interdependencies matter; thus, dynamic feedbacks across countries are possible. This characteristic greatly expands the types of interactions that the empirical model can account for and increases the realism of the experiment in terms of evaluating the responses of EEs to adverse scenarios that affect AEs. Third, dynamic relationships are allowed to be country-specific. This feature reduces eventual heterogeneity biases, and it allows for the evaluation of similarities and differences across regions or countries.

However, this increased realism of the model has a cost. To illustrate this cost, the system of equations (1) can be rewritten as follows:

$$Y_t = W_t \delta_t + E_t \quad (2)$$

where $W_t = I_N \otimes X_t'$; $X_t = (Y'_{t-1}, Y'_{t-2}, \dots, Y'_{t-p}, 1)'$; I_N is the identity matrix; \otimes stands for the Kronegher product; δ_t is the vector of parameters at time t that contains, stacked, the N rows of the matrix $D_t = (D_{t,1}, \dots, D_{t,p})$ with dimension $N \times Np$ and the column vector C .

3.1.1 Factorization of the coefficient vector δ_t

Without restrictions, at each time t and for each equation, $K = Np + 1$ parameters must be estimated. The number of equations is N ; thus, at each time t , NK parameters (the dimension of δ_t) must be estimated. Thus, without restrictions, there is an overparameterization problem. To solve this problem, one could assume that δ_t does not depend on the unit (country) or that there are no interdependencies across each unit¹⁸. However, neither of these assumptions is attractive for the purposes of this paper, because country-specific time-varying parameters are essential for evaluating the evolution of economic cycle interrelations across regions and across countries over time.

¹⁸ These two options have been adopted in the literature (e.g., see Holts Eakin et al. (1988) and Bilder et al. (2000)).

A more appealing solution of the overparameterization problem is to factorize the vector of parameters δ_t ¹⁹, as proposed by Canova and Ciccarelli (2009). The vector δ_t is expressed as a linear combination of a new set of parameters θ_t , which is a vector whose dimension is strictly lower than the dimension of δ_t ($\dim(\theta_t) \ll \dim(\delta_t)$):

$$\delta_t = \Xi\theta_t + u_t, \quad u_t \sim N_{NK}(0, Z) \quad (3)$$

In eq. (3), u_t is the vector of residuals; Z is assumed to be $Z = \Sigma \otimes V$; and, as is standard in related literature (see Kadiyala and Karlsson 1997), $\Sigma = \Omega$. Given that the factors have similar units, a spherical assumption is adopted on V : namely, $V = \sigma^2 I_K$. Finally, $\Xi = (\Xi_1, \dots, \Xi_F)$, and each Ξ_f , for $f = 1, \dots, F$, is a matrix of dimension $NK \times \dim_f$; $\theta_t = (\theta'_{1t}, \dots, \theta'_{Ft})'$; and each θ_{ft} , for $f = 1, \dots, F$, is a column vector with dimension \dim_f .

For example, the following specification could be defined: $\Xi\theta_t = \Xi_1\theta_{1t} + \Xi_2\theta_{2t} + \Xi_3\theta_{3t}$, where Ξ_1 , Ξ_2 , and Ξ_3 are loading matrices of dimension $NK \times 1$, $NK \times g$, and $NK \times N$, respectively; the scalar θ_{1t} captures movements in the coefficient vector δ_t that are common across all countries; the vector θ_{2t} $1 \times g$ captures movements in the coefficient vector δ_t that are common across the g geographical groups of countries; and the vector θ_{3t} $1 \times N$ captures movements that are specific to the N countries. In this example, $\dim(\theta_t) = 1 + g + N$ and $\dim(\delta_t) = NK$, and so $(1 + g + N)$ must be lower than NK to have useful factorization.

As explained by Canova and Ciccarelli and described in Section 1, the factorization of δ_t is useful from both computational and economic points of view. From a computational perspective, by construction, the factorization of δ_t reduces the number of parameters that need to be estimated. In the above example, instead of needing to estimate NK coefficients, it is sufficient to estimate the $(1 + g + N)$ factors characterizing their dynamics.

From an economic perspective, the factorization decomposes Y_t (i.e., the GDP growth rate cycle) in different components that have an economic interpretation. To illustrate this point, eq. (3) can be substituted into eq. (2). If the residuals in eq. (2) and (3) are assumed to be independent, then:

$$Y_t = \mathcal{W}_t\theta_t + v_t, \quad v_t \sim N_N(0, W_tZW_t' + \Omega) \quad (4)$$

where the vector of residuals is $v_t = W_tu_t + E_t$, and the regressors are $\mathcal{W}_t = W_t\Xi$, namely, the averages of certain right-hand-side variables of the original VAR specification (eq. 1). Economically, with eq. (4), the vector of dependent variables Y_t (i.e., the GDP cycle of each country at time t) is decomposed in, for example, common and country-specific cycle indices. When $\theta_t = (\theta'_{1t}, \theta'_{2t})'$ with θ_{1t} of dimension 1×1 and θ_{2t} of dimension $1 \times N$, $GI_t =$

19 See Canova and Ciccarelli (2009) for more details on the factorization of coefficients and its economic interpretation.

$\mathcal{W}_{1t}\theta_{1t}$ is interpretable as the index of the global cycle common to all countries, and $CI_t = \mathcal{W}_{2t}\theta_{2t}$ is the vector whose elements are interpretable as the country-specific cycle indices. GI_t and CI_t are correlated because the same variables enter in \mathcal{W}_{1t} and \mathcal{W}_{2t} , but they become uncorrelated as the number of countries N increases.

3.1.2 Transition equation

To estimate the model, the empirical specification must be completed with the (prior) assumptions on the transition equation²⁰ of θ_t , namely, the time-evolution of the vector of factors θ_t .

There are different ways in which θ_t can change over time. For instance, structural breaks could be introduced into the model at certain time points. This approach is appropriate and effective if the interrelationship between the countries time-evolves in a discrete fashion. However, the introduction of structural breaks is less effective if the relationship between the countries follows a gradual progression over time, as is generally the case. Under the latter condition, it could be more appropriate to investigate the decoupling phenomenon by assuming that the coefficients can gradually change over time.

In this paper, it was assumed that θ_t evolves over time by following a random walk²¹:

$$\theta_t = \theta_{t-1} + \eta_t, \quad \eta_t \sim N_R(0, B) \quad (5)$$

where the stochastic term η_t in (5) is assumed to be normally distributed. The matrix B ($R \times R$) is a block diagonal matrix, $B \equiv \text{diag}(B_1, \dots, B_F)$, to guarantee the orthogonality of factors, and R is the dimension of θ_t , namely $R = \sum_{f=1}^F \dim_f$.

The completed version of the model with the equation for the economic variables²², the transition equation, and the assumption on the innovations is:

$$Y_t = W_t \Xi \theta_t + v_t \quad (6)$$

$$\theta_t = \theta_{t-1} + \eta_t \quad (7)$$

$$v_t \sim N_N(0, W_t Z W_t' + \Omega) \quad (8)$$

$$\eta_t \sim N_R(0, B) \quad (9)$$

in which the innovations v_t and η_t are assumed to be independent.

To compute the posterior probability density functions (pdf) for the unknowns $\psi = (\theta_0, \Omega, \sigma, B)$, their priors must be specified. To minimize the impact of the prior choices on

²⁰ Known as the “evolution equation” in the jargon of the state space model

²¹ It is well known that the random walk process hits any upper or lower bound with a probability of 1. This implication of the model is clearly undesirable. However, a random walk process is very commonly assumed for the transition equation in papers that use state space models (e.g., Koop and Korobilis (2010), Primiceri (2005), or Canova et al (2007)), because eq. (3) is thought to be in place for a finite period of time and not forever.

²² Known as the “observation equation” in the jargon of the state space model.

the posterior distribution of the indicators, rather loose but proper priors were specified. The discussion of their exact form is shown in Appendix C.

Although the model shown in eq. (6)-(9) may be estimated by either classical or Bayesian methods, the latter method was preferred in this study. The Bayesian approach allows the exact small sample distribution of the objects of interest to be obtained even when T and N are small, as is the case in the present study. Classical estimates are justifiable only when either T or N or both go to infinity. Appendix C provides details on the numerical approach used to compute the posterior distributions.

3.2 Use of the model to investigate the decoupling hypothesis

Through the CA experiments, the above-described Panel VAR model was used to investigate how the resilience of the EEs changed over time. Responses of the EE economic cycles to adverse scenarios that affected the AE cycles were quantified through CA experiments in different years, and the results were compared to identify any tendencies in the changes. According to the procedure in Canova and Ciccarelli (2009)²³, the experiments performed in this paper are the generalized impulse response functions obtained as the difference between the conditional and the unconditional expectation. The conditional expectation is the one the model would have obtained for the GDP of each country based on the hypothesis that the actual GDP growth rates of each AE in the year of a shock were reduced by 1.0 point²⁴ (one-time shock). The unconditional expectation of GDP is the one the model would have obtained based on historical information only, so in the unconditional expectation no other condition was set on the GDP dynamics of the AEs. The responses of these experiments did not have any structural content. For example, it was not possible to determine whether a certain policy had any effect, although this exercise is useful for observing how the resilience of the EEs changed over time.

Three different model specifications were implemented, and the model with the greatest support of the data²⁵ was used to perform the CA exercises. As described in Section 1, the specifications of three models differed from each other in their factorizations. The model specifications included the global factor and the country-specific factors (all three models), together with the group factors (the second model) or the regional factors (the third model).

23 See Canova and Ciccarelli (2012) for an empirical application to the countries of the Mediterranean basin.

24 It should be pointed out that data are standardized. This makes coherent the equal weighting scheme in the system (6)-(9) and the comparison across time of the results of the simulations.

25 In Bayesian econometrics, the model j is preferred to the model j^* if the ratio of the marginal likelihoods $\int \ell_j(\alpha_j; Y)P(\alpha_j)d\alpha_j / \int \ell_{j^*}(\alpha_{j^*}; Y)P(\alpha_{j^*})d\alpha_{j^*}$ is greater than 1 (when the same probability is assigned to each model, as it is in this paper), where the function $\ell_j(\alpha_j; Y)$ is the likelihood under the model j and $P(\alpha_j)$ is the prior probability density function of the parameters of model j , and mutatis mutandis for $\ell_{j^*}(\alpha_{j^*}; Y)$ and $P(\alpha_{j^*})$. For details, see Lancaster (2005), for example, among others.

3.3 Results

The first step was to determine which of the three models was most supported by the data. According to the marginal likelihood calculations²⁶, the model specification with the global, country-specific, and regional factors (the third model) was preferable to the other two models, because the log of Bayes factors were 30.2 (when the first model and the third one are compared) and 20.2 (when the second model and the third one are compared). On the basis of Jeffreys Guidelines²⁷, it can be said that data gave “decisive support” for the model with regional factors. Although one might think that the specification with regional factors received the greatest support from the data because it allowed for more degrees of freedom, this was not the case. When the first model was compared against the second model, the log of Bayes factor (12.0) discriminated in favour of the model with fewer degrees of freedom. Table 1 reports the marginal likelihood in logarithmic terms. Thus the data indicates the greater importance of the geographic factor, compared with the group factor (EEs, DEs and AEs), in the breakdown of the economic cycle of each country; nevertheless, it should be pointed out that the subdivision by geographical area, that is, according to the continent to which each country belongs, substantially reflects the geographical distribution of EEs and EAs as well, with the former concentrated prevalently in Latin America and Africa, for example. So, the geographical division largely reflects the division between EEs and EAs²⁸. This observation leads us to

Table 1. Estimated Log marginal likelihood of models.			
Model	Global cycle plus Country Specific cycles plus Regional cycles	Global cycle plus Country Specific cycles plus Group cycles	Global cycle plus Country Specific cycles
Harmonic Mean	-14060	-14093	-14080

believe that, despite data favouring the model in which a part of the economic cycle of each country is assumed to be represented by the specific component of each geographical area, rather than the specific component of the EEs and the EAs groups, one cannot unequivocally and categorically conclude that a country’s belonging to the EEs, rather than to the group of EAs, is irrelevant in defining the components of the economic cycle of the country itself²⁹.

All of the results presented in the remainder of this paper were derived from the model with the global, country-specific, and regional factors (the third model).

²⁶ Marginal likelihoods are computed as harmonic mean (Newton and Raftery, 1994).

²⁷ See Greenberg (2008), pp. 35.

²⁸ In the sample used, 78% of AEs are located in the Europe Region, the 66% of EEs is in LA and Asia Regions (44% and 22% respectively) and the 70% of DEs is located in the SSA region.

²⁹ One interesting extension of the study will be to consider both the regional factor and the group factor in one single model, and to ascertain whether both components are in fact significant.

3.3.1 Global and regional cycles

Figure 3 displays the median (black line) and the posterior credible interval (0.95 and 0.05 percentiles, blue lines) of the global cycle indicator (panel 1) and the regional cycle indicators (from panel 2 to 8). The global cycle indicator reflected the most important economic facts of the past four decades: the positive cycle of the early 1970s and the deep recession of the mid-1970s after the first oil price shock; the recession of the early 1980s, due to different forces, including the tight monetary policies of major industrialized nations and the debt crisis; the mild recession of the early 1990s; the 2000 recession, after the collapse of the “dot-com bubble”, and the subsequent recovery; and the global recession associated with the latest financial crisis (the worst recession since the mid-1970s), with an early rebound in 2010.

Consistent with other studies, fluctuations in oil prices seemed to be related to turning points of the global economic cycle (see Backus and Crucini, 2000). Significant recessions, as measured by the global cycle indicator, occurred with increases in the price of oil; for example, the major oil price increases of the mid-1970s and early 1980s were associated with global recessions.

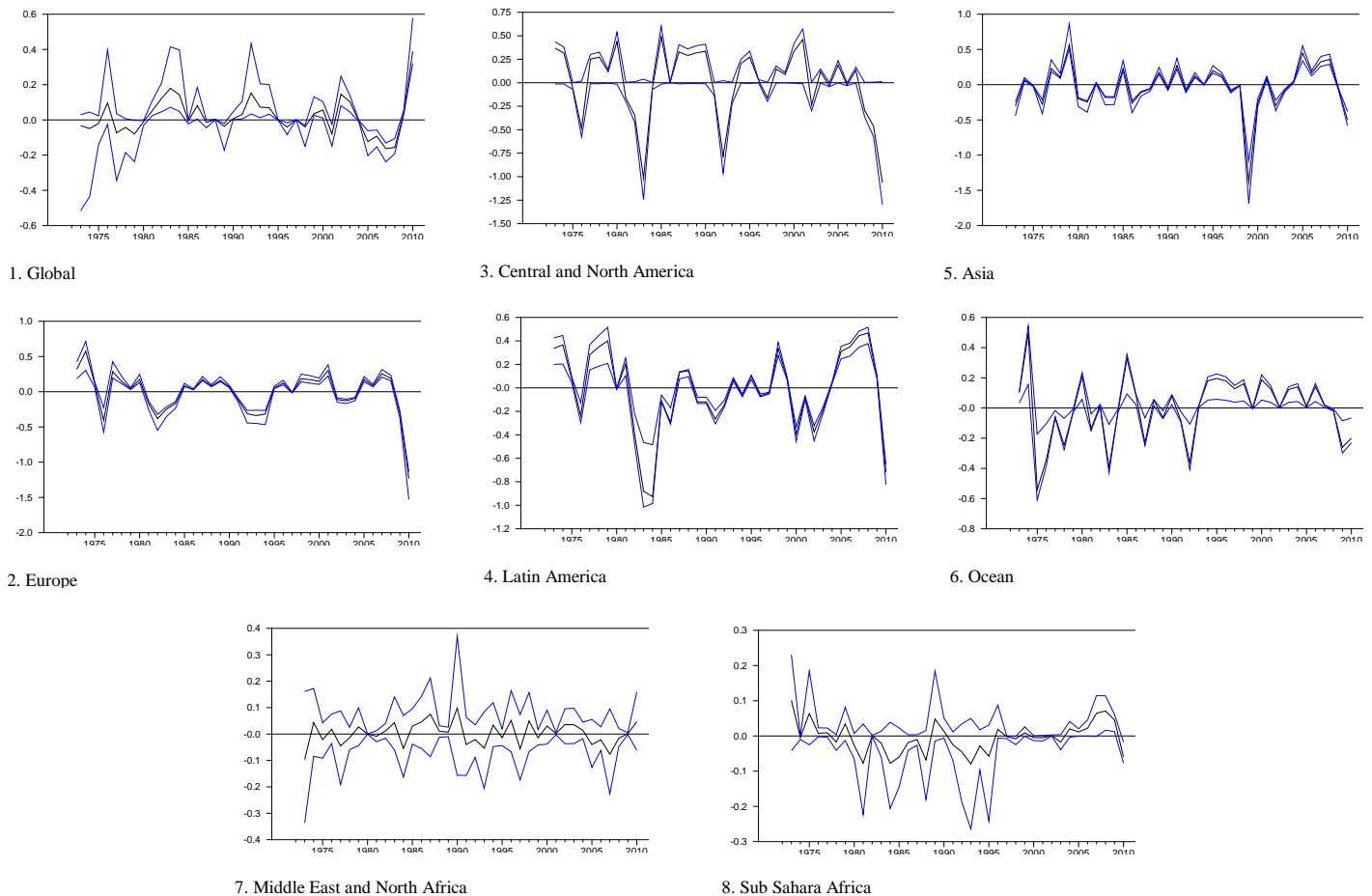


Figure 3. Global and Regional Indicators

The Europe region indicator (panel 2) displayed four recessions from the early 1970s until 2010, which were located at the official CEPR dates for the whole Euro area³⁰. The synchronicity of the cyclical fluctuations in the region showed changes over time. The dispersion was largest around the cyclical trough; namely, the posterior credible intervals were wider at these dates. The most recent recession appeared to be deeper than the three previous ones, because the median value and the credible set were much lower than those of the other occasions.

The Central North America region indicator (panel 3) showed six recessions from the early 1970s until 2010. These recessions were located at the official NBER dates for the USA³¹, with the exception of the 1997 recession, which was actually the smallest recession as measured by the indicator. The recent recession and the recession in early 1980 were the deepest in the sample period. The synchronicity of the cyclical fluctuations in the region did not change over time, and the posterior credible intervals were quite large in the entire sample.

The Latin America region indicator (panel 4) generally showed a persistent cycle with relatively long recessionary periods (e.g., the 1980-1984 period and the “W” recession of 1998-2002). The recent recession that started in 2008 appeared to be deep and almost equal to the recession of the early 1980s, although the regional cycle also showed phases of significantly long expansion (e.g., 2002-2007) and a decade of stagnation (i.e., 1986-1996). The synchronicity of the cyclical fluctuations in this region showed changes over time. Since 1993, the dispersion of the indicator has been lower than that of previous periods (lower posterior credible intervals).

The Asia region indicator (panel 5) showed that the recent recession, which was significantly more shallow than the strong recession of 1999, followed a strong expansion path during the 2002-2008 period. The positive cycle from 2002 to 2008 had just one previous similar period of strong economic expansion during the 1970s; from the early 1980s to the mid-1990s, the economic dynamic was weaker. The synchronicity of the cyclical fluctuations in the Asian region did not change over time, and the posterior credible intervals remained relatively tight in the entire sample.

The Ocean region indicator (panel 6) exhibited at least five recessions in the sample period. The last recession was less strong than the previous one, and the recovery path began recently. The sample period can be divided in two subsamples, 1973-1992 and 1993-2010. The economic cycle appeared to be more persistent in the second than in the first subsample. The posterior credible intervals were quite large in the entire sample.

The MENA indicator and the SSA indicator (panels 7 and 8, respectively) were much less persistent than the cycle indicators of other regions. They displayed numerous ups and

30 Recession dates: 1974Q3-1975Q1, 1981Q1-1982Q3, 1992Q1-1993Q3, 2008Q1-2009Q2.

31 Recession dates: 1973Q-1975Q1, 1980Q1-1980Q3, 1981Q3-1982Q4, 1990Q3-1991Q1, 2001Q1-2001Q4, 2007Q4-2009Q2.

downs, but there were no strong recessions or expansions. In general, for the MENA region, the posterior credible intervals were quite large in the entire sample, whereas for the SSA region, the credible intervals became tighter after 1998.

3.1.2 Path of the resilience of EEs

For each year of the sample period (1981-2010), CAs were performed to compute the responses of EEs³² to shocks spreading from AEs. Both the immediate effect (“impact effect”), that is, the effect felt when the shock actually arises, and the effect felt in each of the subsequent three years following the occurrence of the shock, were computed. By summing the impact effect and that felt in the three years thereafter, we get what we call the cumulative impact. Table 2 presents the median responses of EEs up to the third year after the shock, together with the upper and lower values of the credible intervals (0.95 and 0.05 percentiles, respectively) for different sub-samples of the whole period.

For the sub samples 1983-1995 and 1996-2010, the median immediate responses at time t of all EEs, and the median cumulative responses, have also been plotted in Figure 4, panels 1 and 2. As one can see, the resilience of EEs was higher during the last fifteen years of the period than in the preceding thirteen, both when the evaluation is made in terms of the immediate impact and when it is made in terms of the cumulative impact. During the period 1996-2010, for example, the latter was about 15% lower than it had been in the period 1983-1995.

So, the simulated weaker economic dynamic in the AEs during the 1996-2010 period would have had a softer negative impact on the EEs than would the simulated weaker dynamic in the 1983-1995 period.

	t			$t+1$			$t+2$			$t+3$			Cumulative median impact
	U	M	L	U	M	L	U	M	L	U	M	L	
1983-1995	1.104	-0.134	-1.850	0.950	-0.050	-1.653	1.710	-0.074	-2.203	3.096	-0.136	-4.912	-0.394
1996-2010	1.037	-0.127	-1.622	0.729	-0.044	-1.729	1.940	-0.039	-1.829	2.378	-0.122	-5.681	-0.333
<i>Subsamples</i>													
1981-1985	1.158	-0.154	-1.968	1.085	-0.046	-1.647	1.674	-0.091	-2.322	3.360	-0.140	-4.681	-0.431
1986-1990	1.050	-0.096	-1.628	0.677	-0.060	-1.775	2.015	-0.056	-1.796	2.359	-0.129	-5.902	-0.341
1991-1995	1.108	-0.168	-1.901	1.102	-0.037	-1.578	1.496	-0.072	-2.545	3.938	-0.137	-4.221	-0.413
1996-2000	1.016	-0.105	-1.497	0.644	-0.046	-1.680	1.949	-0.030	-1.658	2.198	-0.123	-5.628	-0.304
2001-2005	1.047	-0.151	-1.694	0.787	-0.040	-1.752	1.965	-0.044	-1.875	2.430	-0.119	-5.728	-0.353
2006-2010	1.037	-0.170	-2.153	0.729	-0.037	-1.849	1.940	-0.055	-2.250	2.378	-0.131	-5.503	-0.393

³² As was explained in subsection 3.2, the responses were obtained as the difference between the conditional and unconditional expectations of $y_{t+\tau}$, $\tau = 0,1,2,3$. In one case, the path of the GDP dynamics of the AEs was conditioned by reducing the actual GDP growth rate of each AE in the year of the shock by 1.0 percentage point (one time shock). In the other cases, no conditions were set on the GDP dynamics of the AEs. The responses were estimated as the medians of 100,000 iterated simulations.

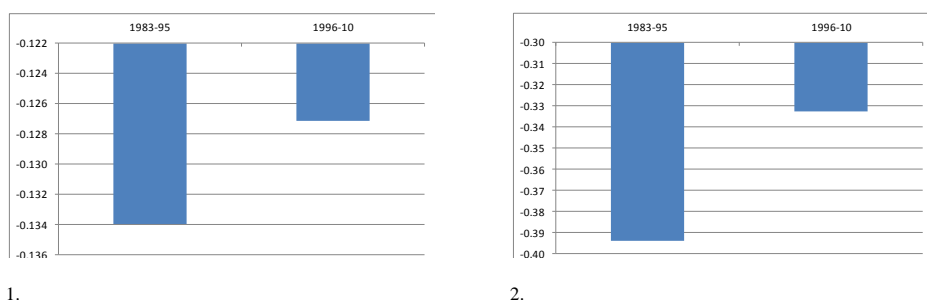


Figure 4 Immediate impact on EEs of shocks spreading from the AEs

The whole sample period has also been broken down into smaller, five-year subsamples, in order to obtain more detailed information on how the EEs' resilience developed, that is, on how the intensity of the impact that a shock from the EAs may produce on the EEs has changed over the course of time. A very interesting fact emerges here. If we observe the last fifteen years of the sample period, we see that the resilience of the EEs fell rather than rose. Indeed, the immediate impact (also shown in Figure 5, panel 1) measured during the five-year period 2006-2010, was up 12% from that measured in the five-year period 2001-2005, and in turn the latter is 40% higher than that measured during the previous five-year period 1996-2000. The same conclusions are reached if the result obtained for the cumulative impact is considered (also reported in Figure 5, panel 2), which increased by 16% from 1996-2000 to 2001-2005, and by 11% from 2001-2005 to 2006-2010. Nevertheless, if we extend the timeframe we see that, despite the increase in the intensity of impacts in the last fifteen years, the cumulative effect of the shock simulated in the five-year period 2006-2010 was approximately 9% lower than that simulated in the five-year period 1981-1985. Therefore, the EEs' resilience at the end of the first decade of the 2000s is higher than it was during the early 1980s.

To assess whether the above results would reflect the behaviour among the subsamples of EEs grouped by geographical area, gli stessi esperimenti fatti per l'intero Gruppo delle EEs sono stati fatti dopo aver raggruppato le EEs per aree geografiche di appartenenza (e.g., Latin American, Asian, MENA, European, and SSA EEs). As with the entire group of EEs, when the timeframe was expanded from the early 1980s to 2010, the increasing resilience of EEs to adverse scenarios affecting AEs was observable, although certain regional peculiarities emerged. In fact, despite the fact that the last fifteen years of the sample period witnessed an

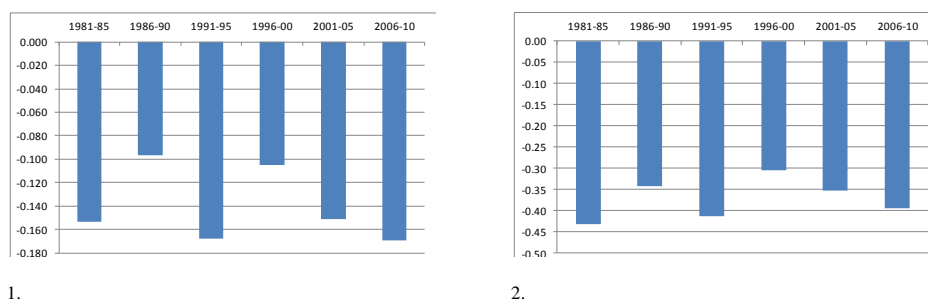


Figure 5 Immediate impact on EEs of shocks spreading from the AEs

increase in the force with which simulated shock impacts the EEs of each geographical area, during the sub-sample 2006-2010 the magnitude of the cumulative impact up to 3 years after a shock, was estimated to be still lower than the impact measured in the sub-sample 1981-1985, with percentages ranging from about 11% in Latin American EEs to 0.4% in SSA EEs (Fig. 6 panel 1).

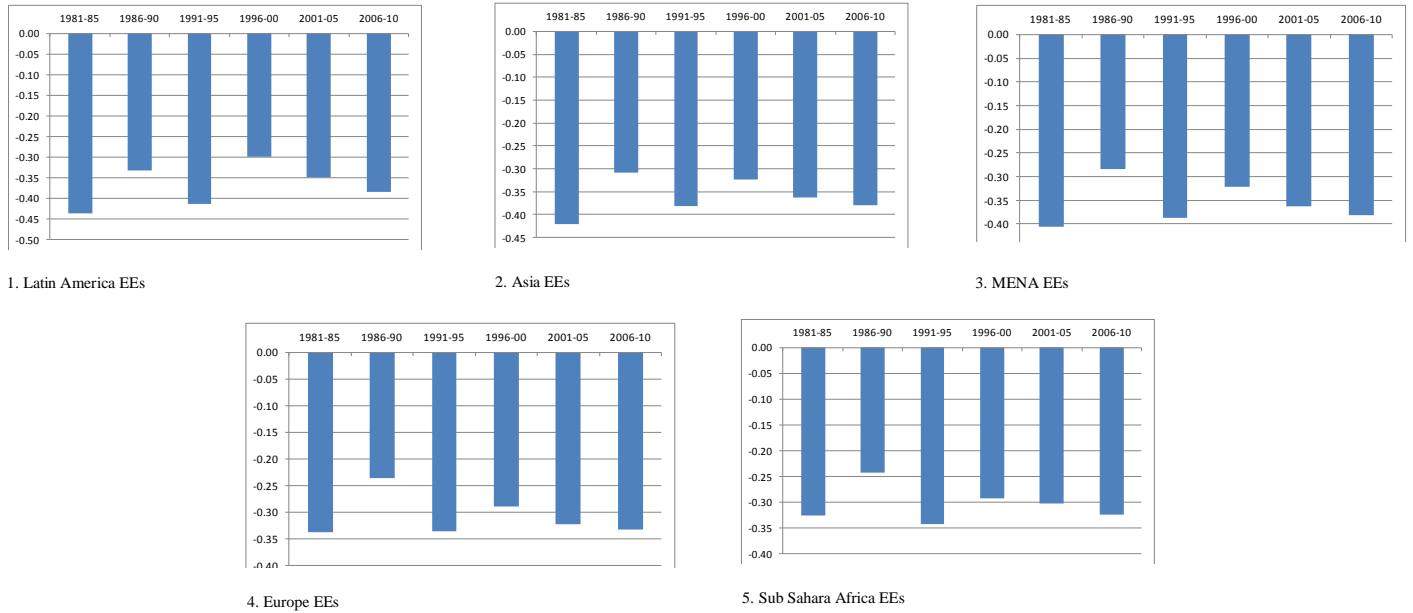


Figure 6 Cumulative impact on EEs (grouped by region) of shocks spreading from the AEs

Table 3 Dynamic impact of the adverse scenario in AEs on:

Latin America EEs	t			$t+1$			$t+2$			$t+3$			Cumulative median impact
	U	M	L	U	M	L	U	M	L	U	M	L	
1983-1995	1.116	-0.131	-1.849	0.952	-0.053	-1.654	1.726	-0.080	-2.235	3.193	-0.129	-5.014	-0.392
1996-2010	1.046	-0.125	-1.625	0.724	-0.050	-1.763	1.988	-0.055	-1.828	2.468	-0.097	-5.978	-0.328
<i>subsamples</i>													
1981-1985	1.173	-0.150	-1.962	1.082	-0.046	-1.651	1.680	-0.092	-2.373	3.508	-0.147	-4.774	-0.436
1986-1990	1.063	-0.093	-1.635	0.673	-0.063	-1.798	2.031	-0.064	-1.827	2.379	-0.112	-6.046	-0.332
1991-1995	1.113	-0.165	-1.897	1.115	-0.046	-1.575	1.501	-0.081	-2.607	4.122	-0.121	-4.237	-0.414
1996-2000	1.029	-0.102	-1.495	0.639	-0.052	-1.718	1.965	-0.042	-1.644	2.273	-0.102	-5.836	-0.298
2001-2005	1.052	-0.150	-1.695	0.785	-0.045	-1.782	2.030	-0.063	-1.874	2.565	-0.091	-6.108	-0.349
2006-2010	1.046	-0.173	-2.152	0.724	-0.045	-1.859	1.988	-0.075	-2.266	2.468	-0.091	-5.799	-0.384
Asia EEs	t			$t+1$			$t+2$			$t+3$			Cumulative median impact
	U	M	L	U	M	L	U	M	L	U	M	L	
1983-1995	1.114	-0.133	-1.847	0.946	-0.044	-1.655	1.729	-0.069	-2.219	3.095	-0.118	-5.070	-0.364
1996-2010	1.028	-0.130	-1.616	0.722	-0.047	-1.725	2.004	-0.053	-1.781	2.383	-0.114	-5.558	-0.344
<i>subsamples</i>													
1981-1985	1.176	-0.155	-1.965	1.101	-0.037	-1.648	1.694	-0.087	-2.402	3.621	-0.141	-4.605	-0.421
1986-1990	1.054	-0.094	-1.627	0.664	-0.052	-1.782	2.011	-0.045	-1.761	2.412	-0.116	-5.934	-0.309
1991-1995	1.109	-0.168	-1.899	1.094	-0.041	-1.578	1.480	-0.075	-2.587	3.498	-0.098	-4.366	-0.382
1996-2000	1.011	-0.108	-1.481	0.620	-0.050	-1.668	1.967	-0.041	-1.580	2.272	-0.125	-5.553	-0.324
2001-2005	1.040	-0.155	-1.689	0.795	-0.043	-1.753	2.086	-0.061	-1.870	2.433	-0.104	-5.451	-0.363
2006-2010	1.028	-0.175	-2.150	0.722	-0.040	-1.865	2.004	-0.072	-2.251	2.383	-0.093	-5.574	-0.380
MENA EEs	t			$t+1$			$t+2$			$t+3$			Cumulative median impact
	U	M	L	U	M	L	U	M	L	U	M	L	
1983-1995	1.120	-0.138	-1.854	0.949	-0.044	-1.673	1.657	-0.071	-2.324	3.073	-0.096	-5.281	-0.350
1996-2010	1.034	-0.136	-1.623	0.731	-0.050	-1.761	1.933	-0.059	-1.904	2.362	-0.098	-5.727	-0.343
<i>subsamples</i>													
1981-1985	1.187	-0.162	-1.975	1.106	-0.036	-1.664	1.612	-0.088	-2.559	3.562	-0.121	-4.878	-0.407
1986-1990	1.058	-0.097	-1.632	0.664	-0.052	-1.804	1.936	-0.050	-1.827	2.267	-0.085	-6.038	-0.284
1991-1995	1.111	-0.174	-1.902	1.102	-0.044	-1.592	1.408	-0.082	-2.677	3.552	-0.087	-4.748	-0.387
1996-2000	1.010	-0.112	-1.489	0.630	-0.053	-1.678	1.892	-0.047	-1.722	2.262	-0.111	-5.639	-0.322
2001-2005	1.048	-0.161	-1.695	0.800	-0.046	-1.804	1.982	-0.068	-1.995	2.303	-0.089	-5.764	-0.364
2006-2010	1.034	-0.186	-2.158	0.731	-0.045	-1.890	1.933	-0.080	-2.359	2.362	-0.072	-5.666	-0.382
Europe EEs	t			$t+1$			$t+2$			$t+3$			Cumulative median impact
	U	M	L	U	M	L	U	M	L	U	M	L	
1983-1995	1.110	-0.136	-1.853	1.026	-0.033	-1.582	1.464	-0.056	-2.391	2.924	-0.070	-4.931	-0.295
1996-2010	1.032	-0.139	-1.619	0.801	-0.041	-1.650	1.578	-0.049	-2.077	2.471	-0.069	-5.075	-0.299
<i>subsamples</i>													
1981-1985	1.179	-0.162	-1.969	1.195	-0.023	-1.587	1.438	-0.077	-2.608	3.689	-0.076	-4.385	-0.338
1986-1990	1.051	-0.098	-1.612	0.698	-0.045	-1.694	1.612	-0.021	-1.925	1.722	-0.071	-5.501	-0.235
1991-1995	1.096	-0.174	-1.905	1.194	-0.025	-1.474	1.235	-0.067	-2.700	3.880	-0.070	-4.435	-0.336
1996-2000	0.998	-0.120	-1.490	0.687	-0.046	-1.597	1.551	-0.033	-1.878	2.377	-0.090	-4.913	-0.289
2001-2005	1.049	-0.164	-1.689	0.864	-0.038	-1.656	1.612	-0.069	-2.139	2.345	-0.051	-4.914	-0.322
2006-2010	1.032	-0.181	-2.173	0.801	-0.036	-1.828	1.578	-0.081	-2.493	2.471	-0.034	-5.159	-0.333
Sub Sahara Africa EEs	t			$t+1$			$t+2$			$t+3$			cumulative median impact
	U	M	L	U	M	L	U	M	L	U	M	L	
1983-1995	1.117	-0.130	-1.848	1.063	-0.032	-1.532	1.437	-0.052	-2.341	2.957	-0.081	-4.230	-0.295
1996-2010	1.046	-0.129	-1.615	0.849	-0.032	-1.607	1.692	-0.026	-2.027	2.506	-0.109	-4.697	-0.296
<i>subsamples</i>													
1981-1985	1.200	-0.155	-1.968	1.261	-0.018	-1.521	1.388	-0.070	-2.525	3.837	-0.083	-3.744	-0.325
1986-1990	1.051	-0.093	-1.606	0.711	-0.045	-1.641	1.616	-0.021	-1.991	1.700	-0.083	-5.189	-0.242
1991-1995	1.112	-0.167	-1.894	1.224	-0.028	-1.417	1.259	-0.064	-2.662	4.251	-0.082	-3.759	-0.343
1996-2000	1.012	-0.112	-1.479	0.716	-0.040	-1.561	1.715	-0.011	-1.752	2.451	-0.129	-4.645	-0.293
2001-2005	1.062	-0.152	-1.690	0.937	-0.021	-1.599	1.671	-0.037	-2.157	2.578	-0.093	-4.535	-0.303
2006-2010	1.046	-0.169	-2.173	0.849	-0.022	-1.731	1.692	-0.050	-2.371	2.506	-0.083	-4.883	-0.324

Note: M stands for median, U and L stand for upper and lower values of the credible interval, respectively (0.95 and 0.05 percentiles).

4. Conclusion

The decoupling hypothesis states that the degree of economic cycle interdependence between EEs and AEs has decreased in recent years. If this idea is true, then 1) the synchronicity of the economic cycles of EEs and AEs should be lower in the last year compared to the previous period, and 2) the resilience of EEs to adverse scenarios affecting AEs should have increased over time. This paper aims to contribute to the continuing debate on decoupling by searching for empirical evidence of these two consequences of decoupling. The economic cycles of 112 countries (23 AEs, 59 EEs, and 30 DEs), covering more than 85% of the world's GDP (at PPP) and more than 90% of the world's population, were studied by two different tools for the empirical investigation: the Euclidean distance and the time-varying Panel VAR model.

The Euclidean distance revealed how the synchronicity of economic cycles between EEs and AEs has changed over time, both when considering all of the EEs together and when considering them from a regional perspective. In general, the correlation between the economic cycles of EEs and AEs increased from the latter half of the 1970s up to the early 2000s, and it was not until the latter half of the 2000s that signs began to emerge of a possible inversion in this trend. This result was consistent with the regional figures, although some regional peculiarities emerged. A very significant increase of synchronicity was observed in, for example, Latin American or MENA EEs, whereas an almost-flat path was observed for the European EEs. However, in no case was there a prevailing downward path of synchronicity between the economic cycles of EEs and AEs. These results suggest that there is no clear evidence of decoupling, although, as explained in section 2, the result of the Euclidean distance may be caused not only by the degree of connection achieved between EEs and EAs, but also by any change in the nature of economic shocks over the course of time, as they may have become more or less global in character. Since it is difficult to distinguish between one factor and the other, it was crucial to examine the decoupling hypothesis also by attempting to measure how the influence of EAs on EEs has changed over time, by means of simulation experiments.

The time-varying Panel VAR model with the factorization of coefficients and unit-specific dynamic and cross-country interdependences was used to estimate how the resilience of EEs to external shocks (i.e., adverse scenarios that affect AEs) has changed over time, and to break up the national economic cycle of each country into different components. The specification with the regional factors got a greater support by date than the specification with the group factors, and the results of the counterfactual analyses showed that, despite the fact

that in the last fifteen years EEs became less resilient to external shocks, their degree of resilience is currently still higher than it was in the early 1980s.

Across what is a rather lengthy period of time, the connection between EEs and AEs has changed, with the former now more resilient to adverse scenarios that may arise in the latter. This result lends support to the decoupling hypothesis, however it is equally clear that the decoupling process is a rather complex one, and does not develop in a gradual, constant manner, but tends to evolve in “alternate phases”, with certain phases of greater resilience followed by other periods of diminished resilience, and vice versa. Until now, this discontinuity has been scarcely documented or discussed in the literature, but is a question deserving of greater consideration and more detailed analysis.

This general result, although with some peculiarities, was confirmed by the results of the empirical analysis conducted from a geographical perspective, namely, by grouping EEs by geographical area. Regional characteristics mattered, and need to be explored in depth; this fact was also confirmed by the marginal likelihood calculations, as the data gave decisive support to the model specification that broke up each national economic cycle into global, regional, and country-specific components.

It is widely believed that credit plays a crucial role in the economic dynamics, and in the spread of shocks across countries. Over the past 30 years, the globalization of the banking sector, the increase in cross-border ownership of assets, and the rapid development in financial engineering have together increased the inter-dependency of banking and credit markets across country borders. Given the importance of financial variables, it may be interesting to extend the present research by adding financial variables to the quantitative model with time-variable parameters and the factorization of coefficients, in order to evaluate the decoupling phenomenon within the framework of international spillovers in macro-financial linkages.

Appendix A

Set of Countries.

Table A1 Countries.			
Advanced Economies	Emerging Economies		Developing Economies
Australia ^g	Albania ^d	Jamaica ^b	Bangladesh ^c
Austria ^d	Antigua ^b	Jordan ^a	Belize ^a
Belgium ^d	Argentina ^b	Korea Rep ^c	Benin ^f
Canada ^a	Bahamas ^b	Lebanon ^e	Bolivia ^b
Denmark ^d	Bahrain ^e	Macao ^c	Burkina Faso ^f
Finland ^d	Barbados ^b	Malaysia ^c	Burundi ^f
France ^d	Bermuda ^b	Mauritius ^f	Cameroon ^f
Germany ^d	Botswana ^f	Mexico ^b	Congo Rep ^f
Greece ^d	Brazil ^b	Morocco ^e	Cote d'Ivoire ^f
Iceland ^d	Bulgaria ^d	Oman ^c	Ethiopia ^f
Ireland ^d	Chile ^b	Pakistan ^e	Fiji ^g
Italy ^d	China ver1 ^c	Panama ^b	Gambia ^f
Japan ^c	China ver2 ^c	Paraguay ^b	Ghana ^f
Luxembourg ^d	Colombia ^b	Peru ^b	Guinea ^f
Netherlands ^d	Costa Rica ^b	Philippines ^c	Honduras ^b
New Zealand ^g	Dominica ^b	Poland ^d	Kenia ^f
Norway ^d	Dominican Rep ^b	Romania ^d	Madagascar ^f
Portugal ^d	Ecuador ^b	Singapore ^c	Malawi ^f
Spain ^d	Egypt ^e	South Africa ^f	Mali ^f
Sweden ^d	El Salvador ^b	Sri Lanka ^c	Mauritania ^e
Switzerland ^d	Gabon ^f	St. Kitts & Nevis ^b	Nepal ^c
United Kingdom ^d	Grenada ^b	St. Lucia ^b	Nicaragua ^b
United States ^a	Guatemala ^b	St. Vincent & Granadine ^b	Nigeria ^f
	Hong Kong ^c	Syria ^e	Rwanda ^f
	Hungary ^d	Thailand ^c	Sierra Leone ^f
	India ^c	Trinidad & Tobago ^b	Swaziland ^f
	Indonesia ^c	Tunisia ^e	Tanzania ^f
	Iran ^e	Turkey ^d	Vietnam ^c
	Israel ^e	Uruguay ^b	Zambia ^f
		Venezuela ^b	Zimbabwe ^f

Notes: a) Central North America; b) Latin America; c) Asia; d) Europe; e) Middle East and North Africa; f) Sub-Saharan Africa; g) Oceania. According to the procedure in Pritchett (2000), AEs are primarily by their pre-1990 membership in the Organization for Economic Cooperation and Development. All other economies are classified as EEs or DEs. The DEs are defined as those that are currently eligible for concessional IMF loans. Remaining countries are classified as EEs. This classification scheme implies that some economies currently classified as AEs by the WEO (2012) are classified as EEs in this article. In line with Abdul Abiad et al. (2012), this classification is appropriate, as those countries have likely acted more like EEs than AEs over the past 40 years.

Appendix B

Euclidean distance computed on economic cycles defined as “deviation cycles”.

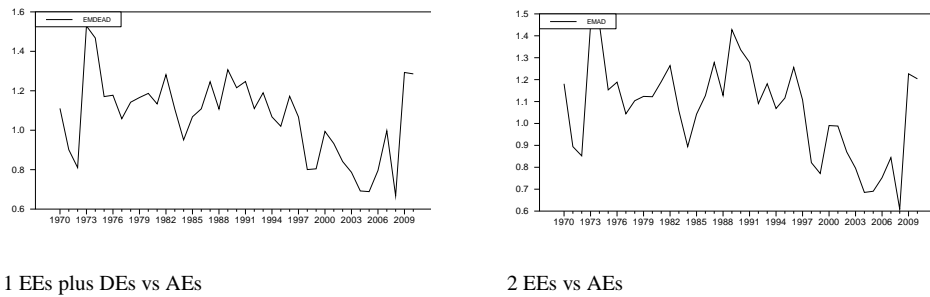


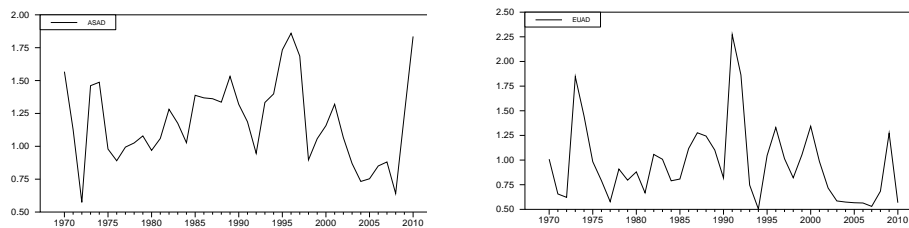
Fig. 1B Euclidean distance computed on deviation cycles: all EEs and DEs vs. all AEs; all EEs vs. all AEs



1. Latin America EEs vs AEs

2. MENA EEs vs AEs

3. Sub Sahara Africa EEs vs AEs



4. Asia EEs vs AEs

5. Europe EEs vs AEs

Fig. 2B Euclidean distance computed on deviation cycles: EEs regional groups vs. all AEs

Appendix C

The priors

The prior distributions proposed in this paper are chosen according to previous experiences from related literature and because of their intuitiveness and convenience in the applications. To compute the distributions of posteriors for parameters in equations (6)-(9), prior densities are assumed for $\xi = (\theta_0, \Omega, B)$, and σ^2 is assumed to be known. The matrix B is the variance/covariance matrix of the innovation η_t .

To guarantee orthogonality of factors, the matrix B must be block-diagonal, hence, $\underset{R \times R}{B} \equiv \text{diag} \left(\underset{dim_1 \times dim_1}{B_1} \quad \cdots \quad \underset{dim_F \times dim_F}{B_F} \right)$, $R \equiv \sum_{f=1}^F dim_f$. Each block B_f for $f = 1, \dots, F$ is assumed to be $B_f = b_f I_f$, where I_f is the identity matrix with dimension dim_f , and b_f is a scalar that is distributed like an inverse gamma with shape parameter $(a/2 = 10^5/2)$ and scale parameter $(b/2 = 0.5)$. Thus, to minimize the influence of the prior choices, relatively loose but proper priors are selected:

$$b_f \sim IG(a/2, b/2) \quad (c1)$$

The matrix Ω with dimension $(N \times N)$ is the variance/covariance matrix of the residuals E_t and so Ω^{-1} is the precision matrix. In Bayesian statistics, the Wishart³³ (W) distribution is often used as the prior for the precision matrix. In this work, it is assumed that the matrix Ω^{-1} has the W distribution with z_1 degrees of freedom and scale matrix Q_1 , namely:

$$\Omega^{-1} \sim W_N(z_1, Q_1) \quad (c2)$$

In this case, z_1 is set equal to $N + 50$ (i.e., dimension of the squared matrix Ω plus 50) because, for the W distribution to be proper, the degrees of freedom must be³⁴ at least equal to the dimension of the matrix Ω . In related literature (e.g., Cogley and Sargent (2001, 2003), Cogley (2003), Primiceri (2005), or Canova et al. (2007)), the scale matrices are chosen to be the inverse of variance/covariance matrix of the corresponding Ordinary Least Squares (OLS) estimates on a training sample. In this paper there is not a training sample and the scale matrix has been set equal to the identity matrix. This prior assumption means that the prior expected variance covariance matrix of residuals is a diagonal matrix, namely uncorrelated residuals between equations, and all equal elements on the diagonal. The prior pdf on Ω allows for posterior non diagonal matrix, namely the case of posterior correlated residuals between equations. The sensitivity of the results to alternative priors parameters, which allow for more

³³ The Wishart distribution is a probability distribution of symmetric positive-definite random matrices, see Greenberg (2008) pag. 190.

³⁴ See Greenberg (2008) pag. 190.

disperse elements of the matrix Ω , has also been checked performing additional simulation experiments.

The initial state θ_0 is assumed to be normally distributed, $P(\theta_0|\mathcal{F}_{-1}) = N_R(\bar{\theta}_0, \bar{V}_0)$ where \mathcal{F}_{-1} is the information available at time $t - 1$. In the related literature (e.g., Primiceri (2005) or Canova et al. (2007), Canova and Ciccarelli (2009), $\bar{\theta}_0$ is the OLS point estimate in the time-invariant version of the system (1). Canova et al. (2005, 2009) assume \bar{V}_0 to be the identity matrix. The sensitivity of the results to other prior parameters \bar{V}_0 is checked through additional simulation experiments. The choice of the prior parameters for the initial state is innocuous. Much flatter specifications of the prior (e.g., with variances 10 or 20 times bigger) deliver the same results.

The elements of ξ are assumed to be independent. They are the initial state of the coefficients in system (1) and the parameters of the pdfs of the innovations v_t and η_t in eq. (3) and (4). Hence, the assumption of independencies is very reasonable and, in fact, is a very common assumption in the related literature; therefore,

$$P(\theta_0, \Omega, B) = P(\theta_0)P(\Omega) \prod_f P(b_f) \quad (c3)$$

Because the in-sample fit improves if σ^2 tends to zero, an exact factorization of δ_t is used.

As showed by Canova et al. (2007), the prior for θ_0 and the law of motion for the coefficient factors imply that the prior for θ_t is $P(\theta_t|\mathcal{F}_{t-1}) = N(\bar{\theta}_{t-1|t-1}, \bar{V}_{t-1|t-1} + B)$.

By combining the priors with the likelihood function of parameters and using the Bayesian rule, it is possible to obtain the posterior conditional density functions of the unknown $\psi = (\Omega, b_f, \{\theta_t\}_{t=1}^T)$. In other words, by denoting $\psi_{-\chi}$, where the vector ψ excludes the parameter χ , $P(\Omega|Y_1, \dots, Y_T, \psi_{-\Omega})$, $P(B|Y_1, \dots, Y_T, \psi_{-B})$, and $P(\theta_t|Y_1, \dots, Y_T, \psi_{-\theta_t})$ can be used for sampling in the Gibbs sampling algorithm.

The posterior distribution and the computational method

The model is a normal linear regression model. As can be seen in, for example, Canova et al. (2007), by combining the priors with the likelihood, which is proportional to

$$L(\psi|Y_1, \dots, Y_T) \propto |\Omega|^{-T/2} \exp \left[\frac{-1}{2} \sum_t (Y_t - W_t \Xi \theta_t)' \Omega^{-1} (Y_t - W_t \Xi \theta_t) \right] \quad (c14)$$

the conditional distributions of interest can be obtained:

$$\Omega^{-1}|Y_1, \dots, Y_T, \psi_{-\Omega} \sim W(z_1 + T, (Q_1^{-1} + \sum_t (Y_t - W_t \Xi \theta_t) (Y_t - W_t \Xi \theta_t)')^{-1}) \quad (c15)$$

$$b_f|Y_1, \dots, Y_T, \psi_{-b_f} \sim IG \left(\frac{a+T \cdot \dim_f}{2}, \frac{b + \sum_t (\theta_{ft} - \theta_{ft-1})' (\theta_{ft} - \theta_{ft-1})}{2} \right), f = 1, \dots, F \quad (c16)$$

$$\theta_t|Y_1, \dots, Y_T, \psi_{-\theta_t} \sim N(\bar{\theta}_{t|T}, \bar{V}_{t|T}), \quad t \leq T \quad (c17)$$

where $\bar{\theta}_{t|T}$ and $\bar{V}_{t|T}$ are the one-period-ahead forecasts of θ_t and the variance/covariance matrix of the forecast error, respectively, calculated with the Kalman smoother, as described in Chib and Greenberg (1995).

The posterior density functions (c15) – (c17) can be used for sampling in the Gibbs sampling algorithm³⁵, as follows:

1. For the value of the hyperparameters and the starting value of $\Omega^{(0)}$ $B^{(0)}$, choose the corresponding OLS estimate in the time-invariant version of the model and the matrix with all of the diagonal elements equal to 0.1 and zero elsewhere, respectively.

2. At the first iteration, draw

$\theta^{(1)} = (\theta_1^1, \theta_2^1, \dots, \theta_T^1)$, sampled with the Kalman smoother knowing $\Omega^{(0)}$ and $B^{(0)}$

$\Omega^{(1)}$ from the conditional posterior distribution $P(\Omega|Y_1, \dots, Y_T, \theta^{(1)}, B^{(0)})$

$b_f^{(1)}$ from the conditional posterior distribution $P(b_f|Y_1, \dots, Y_T, \theta^{(1)}, \Omega^{(0)})$, $f = 1, \dots, F$

3. At the g^{th} iteration, draw

$\theta^{(g)} = (\theta_1^g, \theta_2^g, \dots, \theta_T^g)$, sampled with the Kalman filter knowing $\Omega^{(g-1)}$ and $B^{(g-1)}$

$\Omega^{(g)}$ from $P(\Omega|Y_1, \dots, Y_T, \theta^{(g)}, B^{(g-1)})$

$B^{(g)}$ from $P(B|Y_1, \dots, Y_T, \theta^{(g)}, \Omega^{(g-1)})$

until the desired number of iterations is obtained.

By using the draws, the posterior distributions of coefficients can be estimated by kernel methods and, in turn, the posterior distributions of the indicators can be obtained. For example, the posterior mean of the indicator GI_t can be approximated by $(1/G) \sum_{g=1}^G \mathcal{W}_{1t} \theta_{1t}^g$ and a credible 68% interval can be obtained by ordering the draws of $\mathcal{W}_{1t} \theta_{1t}^g$ and taking the 16th and the 84th percentiles of the distribution.

The convergence of the sampler to the posterior distribution is checked by increasing the length of the chain. The results presented in this paper are based on 100,000 runs of 200 elements drawn 500 times, and the last observation of the final 450 times is used for inference.

³⁵ Gibbs sampling is a simulation tool for obtaining samples from a joint density function through the conditional density functions associated with it. Such samples may be “marginalized”, providing samples from the marginal distributions associated with the joint density function. See Gelfand (2000) for more details on Gibbs sampling.

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