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The international (spillovers in) macro-financial linkages and the decoupling phenomenon

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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. The long-debated question, and even not yet resolved with broad consensus, is whether national economic cycles of emerging and advanced markets are converging or whether they are becoming disconnected, with emerging economies becoming more resilient to shocks that spread from AEs (the so-called "hypothesis of decoupling of EEs from AEs", thereafter simply decoupling). This paper aims to contribute to the debate on the decoupling trying to measure how the resilience of emerging economies to shocks in advanced economies (AEs) has changed over time. It also wishes to identify which type of external shock, real or financial, the EEs are more vulnerable to. To this end, the paper used a time-varying Bayesian panel VAR model, with factorization of the coefficients as proposed by Canova and Ciccarelli (2009), to perform counterfactual experiments over a large sample of countries and over a period of about thirty years. The degree of resilience of EEs was significantly higher in the final part of the sample period (2006-10) compared to the initial part (1986-90), and this is definitely in favour of the decoupling hypothesis, however, the degree of resilience has not changed over time designing a monotone increasing profile, indeed it has changed discontinuously over a period of thirty years, tracing a profile characterized by phases of greater resilience followed by phases of less resilience and vice versa. In the whole sample period the emerging economies are more vulnerable to credit shocks than real ones, moreover this greater relative vulnerability has increased over time getting its peak in the last five years (2006-10).

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1. Introduction

Since 2006-2007, economists have fiercely debated whether national economic cycles are converging, or whether the cycles of EEs and advanced economies (AEs) are becoming disconnected, with EEs becoming more resilient to those shocks spreading from AEs (the so-called "decoupling hypothesis"). The convergence argument is linked to the idea that all economies have become more closely intertwined through trade and finance, which should make the national economic cycles more strongly connected and synchronised. In contrast, the decoupling argument is linked to the issue of the recent substantial development of real and financial linkages among EEs[1] which may have favoured the strengthening of economic linkages within EEs, while at the same time may have favoured their moving away from the AEs.

There is not a precise definition of decoupling, this allows for different interpretation of the phenomenon and so it has been translated in different ways by the economic literature.

First, many authors (e.g. Wälti 2012) speak of a decreasing patterns of correlations between growth of economic variables of different countries, namely a decreasing degree of business cycle synchronization (or comovement).

Second, others authors (e.g. Kose et al., 2008) divide the sources of country's economic fluctuations into global, regional and national factors, and state the decoupling in term of increasing importance over time for national or regional factors in explaining the country's economic fluctuations. Note that, this second way to interpret the decoupling is strictly linked to the first one because decomposing the national economic cycles can be seen as a different way to quantity the synchronization across countries since, as highlighted by Helbling et al. (2007), the contribution of global factor is a measure of the extent of comovement across national business cycles.

Third, the discussions on the decoupling frequently proceed in terms of the size of spillovers from one economy to another (e.g. IMF, World Economic Outlook 2007).

This paper aims to contribute to the debate on the decoupling hypothesis following the last approach. It also intends to identify those external shocks, either real or financial, to which the EEs are most vulnerable.

Has the resilience of the EEs to shocks spreading from the AEs changed during the ongoing period of globalization? If so, has it increased or decreased over time? Are the EEs more vulnerable to real shocks or to financial shocks spreading from the AEs?

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

To address the above questions, the paper used a time-varying panel Bayesian VAR model, with factorization of the coefficients[2] as proposed by Canova and Ciccarelli (2009)[3], on real Gross Domestic Product and real bank lending to the private sector, within a sample of 78 countries (including 21 advanced, 43 emerging, and 14 developing economies [DEs])[4] covering a thirty-year period between 1983 and 2010.

This paper extends the empirical research on the decoupling in different dimensions. First, it considers the bank landing; second, unlike the prevalent literature, this paper does not evaluate the temporal path of the resilience of the EEs to shocks in EAs comparing two sub-periods defined in an arbitrary manner to take account of two period the "pre-decoupling" and the “post-decoupling " one, but rather the sensitivity of EEs is assessed in each year of the entire sample period, third, this paper, unlike the related prevalent literature, does not consider the sensitivity of the EEs to the U.S. or the G7 Group, rather than it evaluates the sensitivity of the EEs in a large set of countries with advanced economies.

The most part of the empirical literature on the decoupling focussed on the GDP growth, as it is one of the main indicator of the economic dynamic of a country, or a set of real indicators such as industrial production, consumption, investment, and financial indicators like stock exchange values for example; instead the bank landing has not been deeply considered though 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, credit has steadily grown in most advanced countries and emerging economies. At the same time, 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. Among the AEs, the external debt -which includes portfolio debt and, in particular, bank lending- remained relatively stable at around 60 per cent of the stock of foreign assets and liabilities. Among the EEs and the DEs, despite the decline in the share of the external debt, at the end of 2007 the external debt still stood at around 40% and 50% respectively[5].

Theoretical studies of credit market friction have highlighted the importance of credit in modelling the inter-linkages between financial markets and the real economy: see, for

[2] 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 the 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).

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

[4] The cited time-varying panel Bayesian model was implemented on the real Gross Domestic Product of a sample of 112 countries (including 23 advanced, 59 emerging, and 30 developing countries) in my previous paper “Is decoupling in action?” (2013), mimeo, to investigate the decoupling hypothesis. The need to extend the model adding credit variables, while sacrificing the extension of the sample of countries, stems from the importance accorded to financial variables in determining the dynamics of the economy of a country and the transmission of shocks from one country to another.

[5] Source: Lane and Milesi Ferretti (2009), "updated and extended version of the External Wealth of Nations Mark II database developed by Lane and Milesi-Ferretti (2007)".

example, Kiyotaki and Moore (1997), Bernanke, Gertler, and Gilchrist (1999), and Gertler and Kiyotaki (2010). The open economy extension of such studies has shown that credit market friction can play an important role in transmitting shocks across countries, through balance sheet linkages among investors and financial institutions: see, for example, Devereux and Yetman (2010).

The time-varying panel Bayesian VAR model used in this paper, with the factorization of the coefficients[6] as proposed by Canova and Ciccarelli (2009)[7], is well-suited to analyse the transmission of shocks from AEs to EEs and to investigate the decoupling hypothesis. First, the use of the factorization of the coefficients it significantly reduces the number of parameters that need to be estimated. This reduction is very important when managing a large dynamic panel, as is the case in this paper. Second, the model specification is particularly useful for investigating how the international transmission of shocks from the AEs to the EEs has changed over time, because the model can account for cross-unit lagged interdependencies. Thus, dynamic feedback across countries and variables is possible. This aspect renders the experiment more realistic in terms of evaluating the response of the EEs to adverse scenarios in the AEs within a global framework. Third, the decoupling is, presumably, more similar to a gradually evolving phenomenon, than to a structural break occurring at a given point in time. Hence the use of time-varying coefficients, rather than the assumption of any structural break in the model coefficients at a given point in time, should be a more appropriate way of studying the decoupling phenomenon.

The empirical investigation was performed in two steps. The first involved the implementation of three different model specifications in terms of their coefficients factorization (i.e., factors). The first model specification included the global factor (i.e., the factor common to all countries) and the country-specific factors. The second model specification added the group factors (i.e., the EEs, the DEs, and the AEs factors) to the global and country-specific factors. The third model specification added regional factors (i.e., factors that were common to countries in the same geographical region, e.g., North and Central America, Latin America, Asia, Middle East and North Africa [MENA], Sub-Saharan Africa [SSA], Oceania, etc.) to the global and country-specific factors.

In the second step, the model specification best supported by the available data, in terms of the estimated marginal likelihood, was used to perform counterfactual analyses (CAs) and to evaluate the reaction of the GDP of EEs' to shocks spreading from the AEs. The intensity of the impact suggests the degree of resilience of the EEs to shocks from EAs, so it

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

can be used as an indicator of EEs' resilience. The CA experiments were implemented for each year of the sample period. The results were compared to determine whether the EEs show a tendency to become more resilient to adverse scenarios in the 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.

This paper is related to the literature on the international transmission of shocks and, above all, it is closely related to the literature on decoupling.

First, it is related to the most recent studies of the international transmission of real and credit shocks. Galesi and Agherri (2009) examine the transmission of regional financial shocks in Europe using a Global VAR framework. Helbling, Huidrom, Kose, and Otrok (2011) examine the impact of global credit shocks on global business cycles, using global factors of credit, GDP, inflation and interest rates, based on data taken from the G-7 countries. They also study the impact of a US credit shock using a FAVAR (factor augmented VAR) model on US GDP and the global factor of GDP, and find that US credit market shocks have had a significant impact on the evolution of global growth during the recent financial crisis.

As can be seen, the existing literature on the international transmission of credit shocks has largely focused on G7 and European economies, while little has been done to study the transmission of the AEs' shocks to emerging market economies. My paper aims to fill this gap and analyse the force with which shocks in the AEs spreads to the EEs and how the force of impact changes over time; moreover it aims to identify those external shocks, either real or financial, to which the EEs are most vulnerable.

Second, this paper is closely related to the most recent research on the decoupling hypothesis, hence to the literature on the historical path of the comovement of economic cycles between the AEs and the EEs (e.g. Kose et al. 2012, or Wälti, 2012) and on the historical path of the sensitivity of the EEs to shocks in AEs (e.g. Guimarães-Filho et al., 2008 or Dèes and Vansteenkiste, 2007)

Kose et al. (2012)[8], following Kose et al. (2003), perform their investigation on a dataset of 106 countries, employing a dynamic factor model[9] to break down the national economic cycles of each country into different components[10]. The conclusion they draw from such variance decomposition analysis is that the global factor became less important for macroeconomic fluctuations in the AEs and the EEs during the period of globalization (from the mid-1980s onwards), whereas the group-specific factor became significantly more important for both the AEs and the EEs.

[8] An earlier version of this article was published by the same authors in NBER Working Paper 14292, 2008.
[9] See Kose et al. (2003) for details on this approach.
[10] Components include the global factor, representing the economic dynamic common to all countries; group factors, representing the economic dynamics common to EE, developing economy (DE), and AE groups, respectively; and country-specific factors, representing the specific economic dynamic of each national economic cycle.

Wälti (2012), in his study of the economic cycles[11] of 30 emerging market economies and 26 advanced market economies, concludes that there has been no decoupling in recent years as the correlation[12] between the economic cycles in the emerging and advanced market economies increased in the latter years of the sample period.

The evolution over time of the magnitude of spillovers was described in Guimarães-Filho et al. (2008) which estimated the US spillovers to Asian emerging economies by the impulse response function performed with the vector autoregressions (VARs). The impulse response functions showed that the impact of US shocks has been lower for the subsample 1980-95 than the following subsample 1996-2007.

Dèes and Vansteenkiste (2007), following Stock and Watson (2003), estimated a Factor-Structural VAR model to explain the GDP growth with the US GDP growth spillovers, the global factor (common international shocks) and the idiosyncratic factor (country specific shocks). They used a dataset covering 23 countries (advanced economies, emerging Asia and emerging Latin America) on quarterly data from 1979(2) to 2003(4) and considered two sub-periods: 1979-1992 and 1992-2003. From their results emerges evidence in favor of the decoupling phenomenon.

As can be seen, different authors got opposing conclusions, and this fact stresses the importance of further investigation.

One of the main conclusions of this paper is that, over the course of the last thirty years, the EEs, despite remaining susceptible to the effects of any shocks spreading from the AEs, have become increasingly resilient to such external shocks, be they of a financial or a real nature. More specifically, the last five years of the period on question (i.e., 1996-2010) have witnessed the greatest resilience of the EEs, whereas during the 1990s and the early 2000s, such resilience was lower than it had been during the 1980s. In general, the results obtained lead us to believe that, over the course of these thirty years, there has been a change in the relationship between the AEs and the EEs which lends support to the decoupling hypothesis, in that it would seem to confirm the belief that the EEs are now more independent from the AEs than they were during the 1980s; nevertheless, if we omit the extreme intervals of the time period in question, and focus also on the intermediate periods, we note that the resilience of the EEs has changed over the course of time in a somewhat discontinuous rather than constant manner, with phases of greater resilience being followed by phases of lesser resilience, and vice-versa. Therefore, the study of decoupling must be based on extended time samples for avoiding misleading. Another interesting result is that during the entire period analysed here, the EEs have been more vulnerable to external shocks of a financial kind than to those of a real kind; moreover, this

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

[12] More precisely, Wälti (2012) proposes an innovative measure of economic cycle interdependence, which is based on the fact that the Euclidean distance between two standardized series conveys the same qualitative information as the correlation coefficient. However, the distance measure has the major advantage that it can be computed on an annual basis, unlike the correlation coefficient that must be estimated over relatively large subsamples of data.

greater relative vulnerability has substantially increased in recent years, reaching its highest ever level during the five-year period 1996-2010.

The rest of the paper is organized as follows. The next section presents the methodology adopted, section 3 discusses the results of the CA experiments, while section 4 presents the conclusions.

2. Methodology

To investigate the decoupling hypothesis I used the time-varying Panel VAR model of the type developed in Canova and Ciccarelli (2009) and Canova et al. (2007).

2.1 The 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; $g = 1, \dots, G$ are variables for each country; $t = 1, \dots, T$ is time; p is the number of lags; y_{it}^{g} is the variable g of country i at time t; y_{it} is a row vector $1 \times G$, $y_{it} = (y_{it}^{1}, \dots, y_{it}^{G})$; $Y_t = (y_{1t}, \dots, y_{Nt})'$ is a column vector with dimension NG; $d_{it,L}$ are row vectors of dimension NG 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:

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

where $D_{t,L}$ is an $NG \times NG$ matrix in which the $i\text{-}th$ 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 $NG \times NG$ 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:

$$Y_t = W_t\delta_t + E_t \tag{2}$$

where $W_t = I_{NG} \otimes X_t'$; $X_t = \left(Y_{t-1}', Y_{t-2}', \dots, Y_{t-p}', 1\right)'$; I_{NG} 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 $D_t = \left(D_{t,1}, \dots, D_{t,p}\right)$ with dimension $NG \times NGp$ and the column vector C.

2.1.1 Factorization of the coefficient vector δ_t

Without restrictions, at each time t and for each equation, $K = NGp + 1$ parameters must be estimated. The number of equations is NG; thus, at each time t, NGK 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 unit[13]. 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.

A more appealing solution of the over-parameterization problem is to factorize the vector of parameters δ_t[14], 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 $\left(dim(\theta_t) \ll dim(\delta_t)\right)$:

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

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 $NGK \times dim_f$; $\theta_t = (\theta'_{1t}, \dots, \theta'_{Ft})'$; 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} $1 \times s$ captures movements in the coefficient vector δ_t that

[13] These two options have been adopted in the literature (e.g., see Holts Eakin et al. (1988) and Bilder et al. (2000)).
[14] See Canova and Ciccarelli (2009) for more details on the factorization of coefficients and its economic interpretation.

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, $dim(\theta_t) = 1 + s + N$ and $dim(\delta_t) = NGK$, and so $(1 + s + N)$ must be lower than NGK 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 NGK coefficients, it is sufficient to estimate the $(1 + s + N)$ factors characterizing their dynamics.

From an economic perspective, the factorization decomposes Y_t 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:

$$Y_t = \mathcal{W}_t\theta_t + \upsilon_t,\ \upsilon_t \sim N_N(0, W_t Z W_t' + \Omega) \tag{4}$$

where the vector of residuals is $\upsilon_t = W_t u_t + E_t$, 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 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_{1t} of dimension $1 \times N$, $GI_t = \mathcal{W}_{1t}\theta_{1t}$ 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.

2.1.2 Transition equation

To estimate the model, the empirical specification must be completed with the (prior) assumptions on the transition equation[15] 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 walk[16]:

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[15] Known as the "evolution equation" in the jargon of the state space model

[16] 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

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

where the stochastic term η_t in (5) is assumed to be normally distributed. The matrix B $(R\text{x}R)$ is a block diagonal matrix, $B \equiv diag(B_1, \dots, B_F)$, 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 variables[17], the transition equation, and the assumption on the innovations is:

$$\begin{cases} Y_t = W_t \Xi \theta_t + \upsilon_t & (6) \\ \theta_t = \theta_{t-1} + \eta_t & (7) \\ \upsilon_t \sim N_N(0, W_t Z W_t' + \Omega) & (8) \\ \eta_t \sim N_R(0, B) & (9) \end{cases}$$

in which the innovations υ_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 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 A provides details on the numerical approach used to compute the posterior distributions.

2.2 The data and the use of the model to investigate the decoupling hypothesis

The Appendix B shows the list of the 78 countries used as sample, and their grouping[18] into EEs, DEs and AEs. These countries cover about 85% of the world's GDP (at PPP) and more than 90% of the world's population. In this paper, the sample period goes from 1983 to 2010, and the growth rate of the real gross domestic product per head at purchasing power

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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.

[17] Known as the "observation equation" in the jargon of the state space model.

[18] All countries of the sample have a rating at least "C" in the Penn World Table ranking. 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.

parity (from now on simply GDP) was used, with data taken from the Penn World Table 7.1[19]. For each country, the World Development Indicators (WDI) of the World Bank is the source of data on domestic credit provided by the banking sector. The credit has been expressed in terms of real growth rate by using the GDP deflator provided by the same source, namely the WDI. All the variables of the system are demeaned and standardized prior to estimation. This makes coherent the equal weighting scheme in (6)-(9) and the analysis of the results.

As described in section 1, three different model specifications were implemented, and the model with the greatest support of the data[20] was used to perform the CA exercises. In particular, the specifications of the 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).

Through the CA experiments, the responses of the GDP in the EEs to financial and real shocks that spread from the AEs were quantified for different sub-period, and the responses were compared to identify any changes. According to the procedure in Canova and Ciccarelli (2009)[21], 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 for each AE the actual growth rate of credit (when you wish to consider the financial shocks) or the growth rate of GDP (when you wish to consider the real shocks) were reduced by 1.0 point in the year for which you intend to simulate a shock (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 credit and 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 very useful to the end of this paper as it allows to observe how the resilience of the EEs to shocks that spread from AEs changed over time.

3. Path of the resilience of EEs

[19] 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.

[20] 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.

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

In this section, counterfactual analyses have been employed to ascertain whether, and to what degree, the resilience of EEs' GDP to shocks spreading from the AEs has changed over time. The first subsection quantifies the effects of the financial shock spreading from the AEs, by simulating a one-point reduction in credit growth rate in the AEs; whereas the second subsection measures the effects on the EEs of a real external shock, by simulating a one-point reduction in the GDP growth rate in the AEs. It should be pointed out that the figures are standardized, and therefore in both cases the variable subjected to the shock witnessed a reduction in its own trend amounting to one standard deviation. The third subsection compared the various ways in which financial and real shocks spread.

First of all, the model needed to be implemented, and so the first step was to determine which of the three models was best supported by the data. According to the marginal likelihood calculations[22], data provided greater support to the model with the global and country-specific factors. Table 1 reports the marginal likelihood in logarithmic terms.

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

Table 1. Estimated Log marginal likelihood of models.

Model	Global cycle plus Country Specific cycles	Global cycle plus Country Specific cycles plus Group cycles	Global cycle plus Country Specific cycles plus Regional cycles
Harmonic Mean	-2558	-3263	-5033

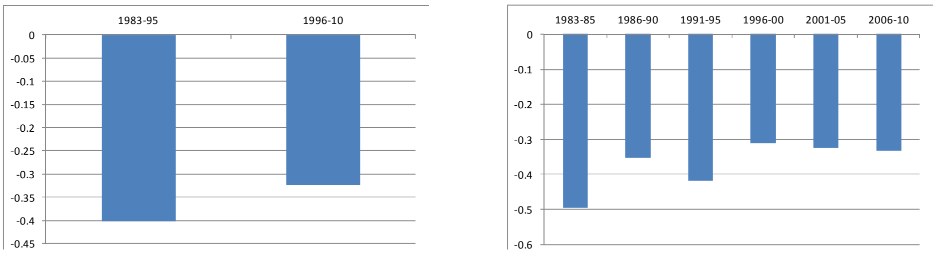
4.1 Spread of credit shocks from the AEs to the EEs

For each year in the period between 1983 and 2010, a calculation was made of the effect that a credit squeeze in the AEs has on the GDP of the EEs. 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 Dynamic impact of the credit shock spreading from AEs to Emerging Economies

	t			t+1			t+2			t+3			cumulative median impact
	U	M	L	U	M	L	U	M	L	U	M	L	
1983-1995	2.777	-0.402	-2.737	3.848	-0.106	-4.031	8.146	-2.996	-14.88	16.26	-0.067	-16.67	-3.571
1996-2010	2.434	-0.324	-2.653	3.476	-0.111	-3.994	4.779	-1.339	-15.03	12.45	-0.178	-16.04	-1.952
Subsamples													
1983-1985	3.122	-0.496	-2.729	2.375	-0.259	-2.935	10.55	-1.155	-7.79	9.215	-0.394	-9.750	-2.304
1986-1990	2.713	-0.353	-2.621	3.250	0.025	-3.250	7.245	-1.550	-12.33	15.91	0.031	-12.25	-1.847
1991-1995	2.666	-0.419	-2.852	5.241	-0.186	-5.288	7.119	-7.688	-21.34	25.13	-0.084	-32.72	-8.377
1996-2000	2.406	-0.312	-2.622	3.829	-0.122	-3.878	3.343	-3.093	-14.03	11.72	-0.407	-10.61	-3.934
2001-2005	2.278	-0.324	-2.481	4.674	-0.126	-6.565	4.422	-3.258	-24.53	22.51	-0.362	-53.99	-4.071
2006-2010	2.434	-0.333	-2.897	3.476	-0.089	-1.620	4.779	-0.267	-5.341	12.46	-0.075	-27.71	-0.764

The median impact for the entire group of EEs, calculated at different times over the whole sample period, is shown in Table 2, together with the upper and lower values of the credible intervals (0.95 and 0.05 percentiles, respectively).



1. 2.

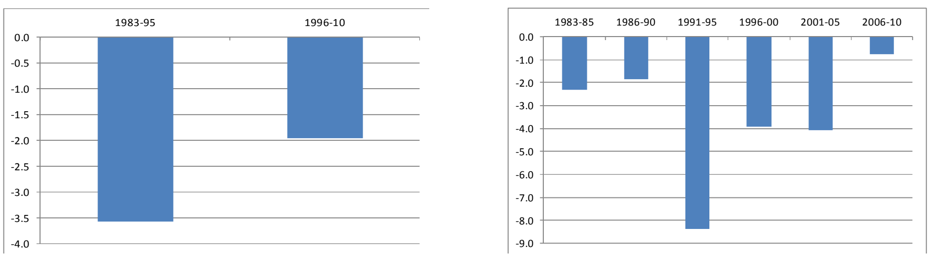
Fig. 1 Immediate median impact of the credit shock spreading from AE sto EEs

The immediate impact effect is also shown in graphical form in Figure 1, panels 1 and 2. If we divide the sample period into two sub-periods, that is, 1983-1995 and 1996-2010, and we compare the results (see Figure 1, panel 1), what we see is that the force of the impact of the credit shock in the AEs on the EEs over the course of the last fifteen years has been about 19% less that it was during the previous thirteen years.

If we break down the sample into smaller sub-periods, we can see that the impact effect over the last five years (shown in Figure 1, panel 2), although basically unchanged from the previous two five-year periods, was less than it was during the early 1980s (by around 33%), and also less than it was during the early 1990s (by around 20%). In other words, the simulated weaker credit dynamic in the AEs during the late 2000s had a softer immediate impact on the EEs than the simulated weaker credit dynamic witnessed at the beginning of the globalization era.

The cumulative median responses, shown in the last column of table 1 and also graphically in Figure 2, have fallen substantially over the last 15 years. In the sub-period 1996-2010, they were estimated to be about 45% lower than over the previous thirteen years. The resilience of the EEs, as can be deduced from the cumulative impact that the simulated credit shock in the AEs has had on the EEs, seems to have been particularly significant during the last five years of the sample period, that is, from 2006 to 2010 (see Figure 2, panel 2), when said impact is smaller than it was in all previous years.

The EEs' resilience to external financial shocks reached its nadir in the early 1990s;



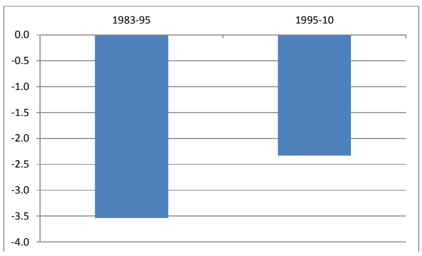
1. 2.

Fig. 2 Cumulative median impact of the credit shock spreading from AEs to EEs thereafter it improved, although it was still lower in the early 2000s than it had been in the 1980s. it was only after this, that is during the period 2006-2010, that a substantial improvement was seen in the resilience of the EEs to external credit shocks; in fact, the cumulative median impact on GDP simulated for the period 2006-2010 was about 58% lower than it had been during the period 1985-1990.

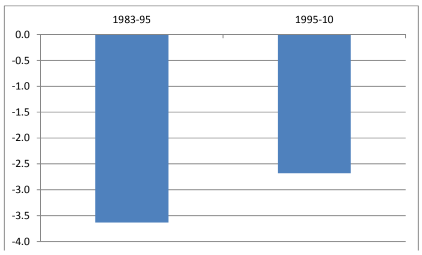
In order to ascertain whether the abovementioned results also reflect evidence to be found at the geographical level, the EEs have been grouped together on the basis of their respective geographical areas (Latin American, Asian, MENA, and SSA). As with the entire group of EEs, the median impact on GDP resulting from credit shocks spreading from the AEs has been calculated for each individual geographical area (see Table C 1 in Appendix C).

In general, the simulations have showed that for all regions the force of the immediate impact and of the cumulative impact (this last also shown graphically in Figure 3, panels 1 to 4) has been smaller in recent years than it was in previous years. If we compare the last fifteen years of the sample period with the previous thirteen years, the magnitude of the cumulative impact have fallen at a rate ranging from about 26% in Asia EEs and MENA EEs to 34% and 38% in the Latin American EEs and SSA EEs respectively.

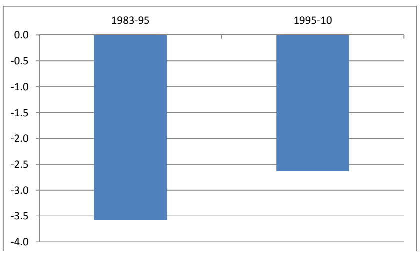
It is very interesting to note that for each of the geographical areas in question, the resilience of the EEs during the 1990s and into the early 2000s was not as great as it had been during the 1980s, whereas the period from 2006 to 2010 witnessed a greater degree of resilience than had been seen in the entire twenty-five year period beforehand (see Figure 4, panels 1 to 4). Even when the EEs were considered on a regional basis, throughout the entire, almost 30-year sample period, their increasing resilience to those adverse credit scenarios affecting the



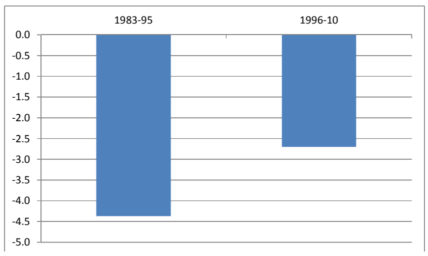
1. Latin America EEs



2. Asia EEs

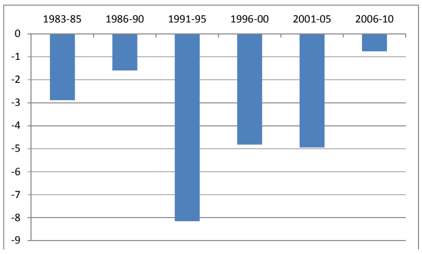


3. MENA EEs

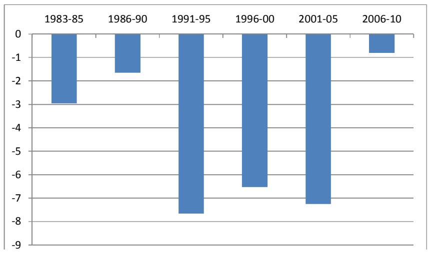


4. SSA EEs

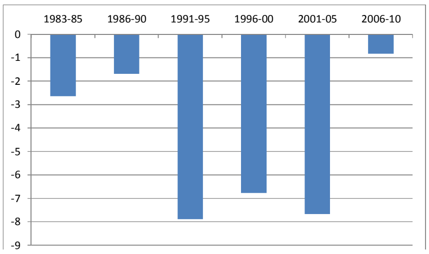
Fig. 3 Cumulative impact of the credit shock spreading from AEs to EEs grouped by regions



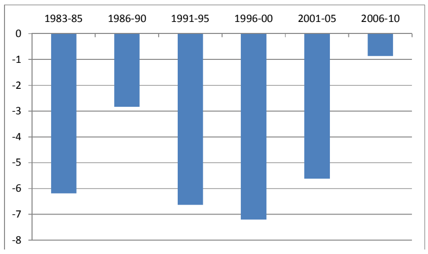
1. Latin America EEs



2. Asia EEs



3. MENA EEs



4. SSA EEs

Fig. 4 Cumulative impact of the credit shock spreading from AEs to EEs grouped by regions

AEs was clear, albeit characterized by certain specific regional peculiarities. If we separate the two extreme and more distant sub-periods, that is, 1986-90 and 2006-10, and we compare them, we see that the impact fell substantially in all regions, at a rate varying from 69% in the SSA EEs to 50% in the MENA EEs.

4.2 Spread of real shocks from the AEs to the EEs

At this point, the same type of analysis as conducted in the previous sub-section was carried out again, but this time rather than analysing a financial shock, a real shock was taken into consideration, consisting in the one-point reduction in the GDP growth rate of the advanced economies.

Table 3 Dynamic impact of the real shock spreading from AEs to Emerging Economies

	t			t+1			t+2			t+3			cumulative median impact
	U	M	L	U	M	L	U	M	L	U	M	L	
1983-1995	2.137	-0.168	-2.062	1.723	-0.057	-1.710	8.053	-1.262	-58.189	75.65	-0.025	-66.54	-1.512
1996-2010	1.848	-0.116	-1.912	1.405	-0.063	-1.604	4.823	-0.416	-52.538	38.51	-0.085	-59.20	-0.679
Subsamples													
1983-1985	2.833	-0.152	-2.593	1.453	-0.056	-1.290	19.413	-0.390	-19.886	35.59	-0.100	-35.53	-0.697
1986-1990	2.086	-0.212	-1.856	1.951	-0.018	-1.800	8.986	-1.062	-68.992	93.39	0.004	-62.79	-1.286
1991-1995	1.845	-0.123	-2.024	1.689	-0.107	-1.937	2.555	-2.477	-69.790	87.85	-0.048	-93.18	-2.754
1996-2000	1.601	-0.112	-1.707	1.690	-0.091	-1.916	1.766	-1.246	-55.220	45.35	-0.158	-86.32	-1.607
2001-2005	1.988	-0.152	-1.872	1.849	-0.090	-2.133	4.433	-1.684	-78.824	71.46	-0.221	-80.44	-2.147
2006-2010	1.848	-0.078	-2.285	1.405	-0.024	-0.840	4.823	-0.038	-6.889	38.51	0.007	-10.50	-0.133

Table 3 shows the median impact for the entire group of EEs, calculated for different periods of time. An analysis of the immediate impact effect reveals that the force of the impact of the simulated AEs' real shock on the EEs over the last fifteen years was 30% lower than that recorded during the previous thirteen years. The cumulative impact was also less substantial during the last fifteen years than it was during the initial thirteen (around 50% less as can be seen from Figure 5 and from the final column in table 3). In order to obtain more detailed information, the entire sample period was broken down into five-year sub-periods, and as with the analysis of the credit shock, also in the case of real shock the results that emerge are rather interesting. First, the five-year period 2006-2010 was the one in which the EEs displayed the greatest resilience to external real shocks. During those years, the cumulative impact of the simulated real external shock was 80% lower than it was in the five-year period 1986-1990. Second, during the 1990s and the early 2000s, the EEs were more vulnerable to external shocks than they had been in the 1980s.

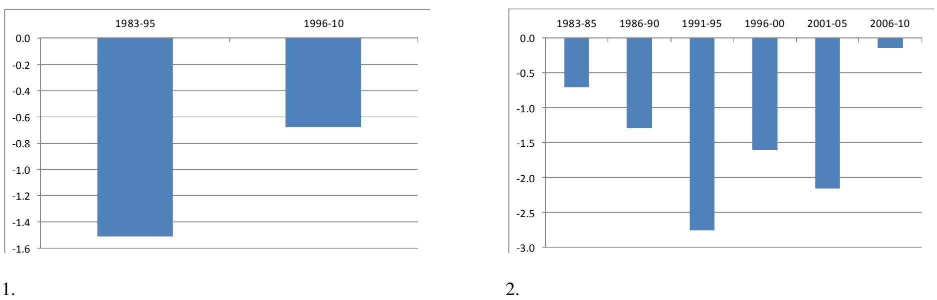


Fig. 5 Cumulative median impact of the real shock spreading from AE sto EEs

In geographical terms, that is, by sub-dividing the EEs into specific geographical areas, what emerges (see Table C 2 in appendix C) is that for all regions, the magnitude of the immediate impact and of the cumulative impact (the latter is also shown graphically in Figure 6) has been lower in recent years than it was in previous years. If we compare the last fifteen

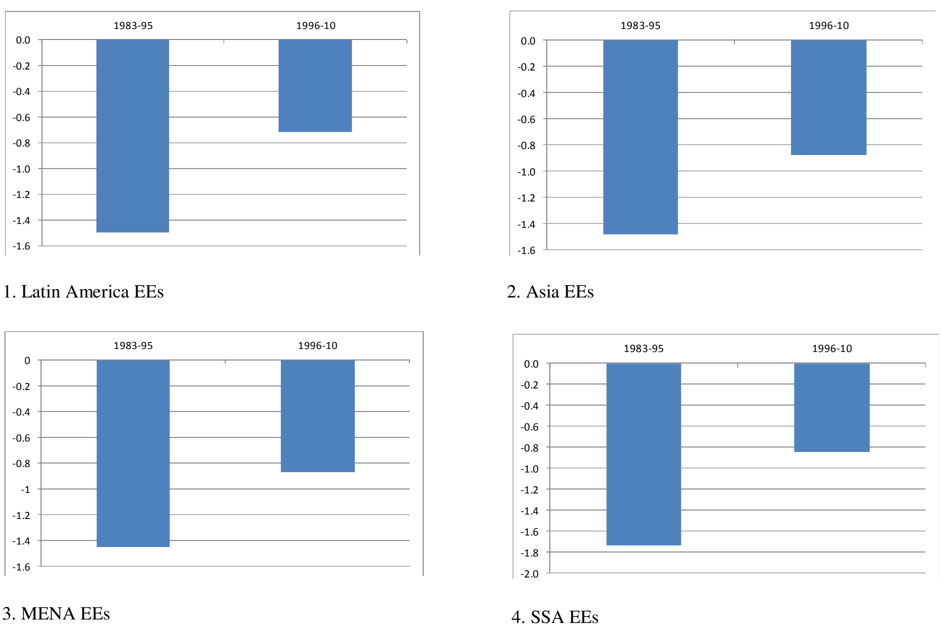
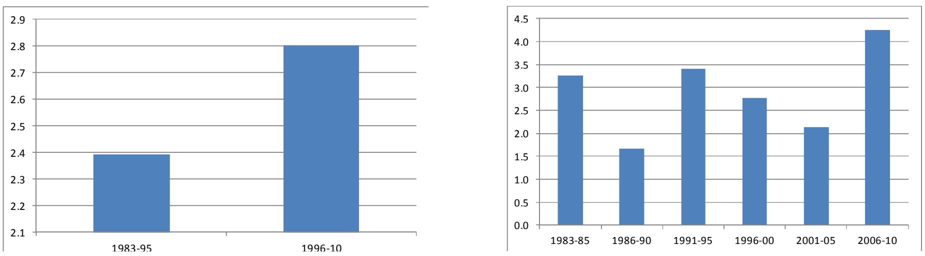


Fig. 6 Cumulative impact of the real shock spreading from AEs to EEs grouped by regions

years of the sample period with the previous thirteen years, the magnitude of the cumulative impact is estimated to have fallen at a rate ranging from 52% in the Latin American EEs to 40% in the MENA EEs (and at rates of 51% in the SSA EEs and of 41% in the Asian EEs).

4.3 What type of shock are EEs more vulnerable to?

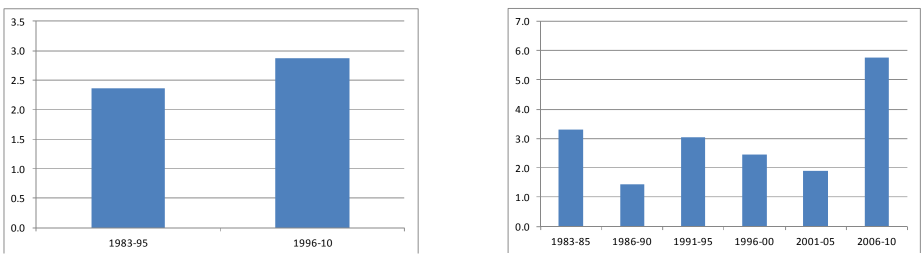
The emerging economies' resilience to external shocks, be they financial or real, seems to have grown in more recent years compared with the initial period of economic globalization. However, this does not mean that the emerging economies have become immune to the effects of any external shocks. So it is natural to demand what kind of external shock – financial or real – such emerging economies are more vulnerable to. Two interesting results emerge with regard to this question. First, throughout the entire sample period, the emerging economies were more vulnerable to financial shocks than to real shocks. Second, this relative vulnerability was greater in the last fifteen years of that period than it was in the previous thirteen years. While the immediate impact of the simulated financial shock during the period 1983-1995 was 2.4 times greater than the impact of the simulated real shock, during the second half of the sample period (1996-2010) this factor rose to 2.8 (see Figure 7, panel 1).



1. 2.

Fig. 7 Ratio immediate impact of credit shock on immediate impact of real shock

This greater relative vulnerability to financial shocks was particularly evident during the last five years of the sample period (2006-2010), when the immediate impact of the financial shock hit its highest value in thirty years, and was more than four times greater than the impact of any real shock (see Figure 7, panel 2), whereas during the early 1980s this multiplying factor was just over three, and just below 3.5 during the early 1990s. The greater vulnerability to financial shocks can be seen not only in the immediate impact, but also in the cumulative impact (see Figure 8, panels 1 and 2).



1. 2.

Fig. 8 Ratio cumulative impact of credit shock on cumulative impact of real shock

5. Conclusion

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 financial and real shocks (i.e., adverse financial and real scenarios affecting AEs and spreading to EEs) has changed over time. The specification including global and the country-specific factors, was better supported by the figures than was the specification also comprising group factors and the specification also comprising regional factors.

The results of the counterfactual analyses show that the resilience of EEs has increased over the last 30 years. In particular, the last five years of the sample period (2006-2010) were those during which the EEs proved more resilient to external shocks of both the financial and real kind. In that period, the cumulative impact of the simulated external credit shock (for up to three years following said shock) on the emerging economies was 58% lower than the impact calculated for the five-year period 1986-1990 (and said impact was around 80% lower in the case of the simulated real shocks). On the other hand, the EEs were more vulnerable to external shocks, whether financial or real, during the 1990s and the early 2000s, than they had been in the 1980s.

The degree of resilience of the EEs, despite being substantially greater during the final part of the sample period (2006-2010) than it had been at the beginning (1986-1990), did not grow constantly during the course of the entire sample period, but changed in a discontinuous manner during this thirty-year period, with certain phases of greater resilience followed by other periods of diminished resilience, and vice-versa. However, in general it appears clear that at the present moment in time, EEs are more resilient to adverse scenarios in the AEs than they have been over the past thirty years. This result lends support to the decoupling hypothesis endorsed in particular by the recent work of Kose et al. (2012).

The empirical evidence that emerges regarding the emerging economies as a whole, basically reflects what is found at the regional level as well, that is, when the EEs are grouped together on the basis of their respective geographical areas. If we compare the last fifteen years of the sample period with the previous thirteen years, the magnitude of the cumulative impact felt up to 3 years after the credit shock is estimated to have fallen at rate ranging from 45% in the Latin American EEs to 36% in the MENA EEs; such percentages range from 52% in Latin American EEs to 40% in MENA EEs in the case of real shock.

To conclude, then, two further interesting results should be pointed out here. During the course of the entire sample period, the EEs were seen to be more vulnerable to credit shocks than to real shocks; moreover, this greater relative vulnerability grew over the course of time, reaching its peak in the last five years of the sample period (i.e. in the years 2006-10), when the immediate impact of the simulated financial shock was more than four times greater than the impact of the simulated real shock. This last result, help us to understand why the recent financial crisis exploded in USA in 2007 quickly became one of the worst global economic crisis of the history.

Appendix A

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, $\underbrace{B}_{RxR} \equiv diag\left(\underbrace{B_1}_{dim_1 x dim_1} \quad \cdots \quad \underbrace{B_F}_{dim_F x dim_F}\right)$, $R \equiv \sum_{f=1}^{F} dim_f$. 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 $\left({}^{a}/_{2} = {}^{10^5}/_{2}\right)$ and scale parameter $\left({}^{b}/_{2} = 0.5\right)$. Thus, to minimize the influence of the prior choices, relatively loose but proper priors are selected:

$$b_f \sim IG\left({}^{a}/_{2},\ {}^{b}/_{2}\right) \qquad (c1)$$

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 Wishart[23] (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:

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

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 be[24] 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

[23] The Wishart distribution is a probability distribution of symmetric positive-definite random matrices, see Greenberg (2008) pag. 190.
[24] 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 υ_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,

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

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 $P(\theta_t|\mathcal{F}_{t-1}) = N\big(\bar{\theta}_{t-1|t-1}, \bar{V}_{t-1|t-1} + B\big)$.

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 $\psi = \big(\Omega, b_f, \{\theta_t\}_{t=1}^{T}\big)$. 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 $P\big(\theta_t|Y_1, \dots, Y_T, \psi_{-\theta_t}\big)$ 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

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

the conditional distributions of interest can be obtained:

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

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

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

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 algorithm[25], 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

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

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

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

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

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

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

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

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 $(1/G) \sum_{g=}^{G} \mathcal{W}_{1t} \theta_{1t}^g$ 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.

[25] 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.

Appendix B

Set of Countries

Table B1 Countries.

Advanced Economies	Emerging Economies		Developing Economies
Australia[g]	Antigua[b]	Jordania[e]	Bangladesh[c]
Austria[d]	Argentina[b]	Korea Rep[c]	Belize[a]
Belgium[d]	Bahamas[b]	Malaysia[c]	Benin[f]
Canada[a]	Bahrain[e]	Mauritius[f]	Burkina Faso[f]
Denmark[d]	Barbados[b]	Mexico[b]	Burundi[f]
Finlandia[d]	Brazil[b]	Morocco[e]	Cameroon[f]
France[d]	Chile[b]	Oman[c]	Fiji[g]
Germany[d]	China[c]	Pakistan[e]	Honduras[b]
Greece[d]	Colombia[b]	Panama[b]	Kenia[f]
Iceland[d]	Costa Rica[b]	Paraguay[b]	Madagascar[f]
Ireland[d]	Dominica[b]	Philippines[c]	Mali[f]
Italy[d]	Dominican Rep[b]	Singapore[c]	Nepal[c]
Japan[c]	Ecuador[b]	South Africa[f]	Nigeria[f]
Luxembourg[d]	Egypt[e]	Sri Lanka[c]	Swaziland[f]
Netherlands[d]	El Salvador[b]	St. Vincent & Granadine[b]	
New Zealand[g]	Gabon[f]	Syria[e]	
Portugal[d]	Grenada[b]	Thailand[c]	
Spain[d]	Guatemala[b]	Tunisia[e]	
Sweden[d]	India[c]	Turkey[d]	
United Kingdom[d]	Indonesia[c]	Uruguay[b]	
United States[a]	Iran[e]	Venezuela[b]	
	Israel[e]		

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 C

Table C 1 Dynamic impact of the adverse credit scenario in AEs grouped on the basis of their geographical areas

	t			t+1			t+2			t+3			cumulative median impact
	U	M	L	U	M	L	U	M	L	U	M	L	
Latin America													
1983-1995	2.744	-0.406	-2.730	4.391	-0.095	-3.755	9.282	-2.983	-16.29	21.54	-0.054	-14.65	-3.539
1996-2010	2.413	-0.329	-2.647	3.411	-0.126	-4.433	5.001	-1.635	-16.15	12.41	-0.240	-21.50	-2.331
Asia													
1983-1995	2.759	-0.402	-2.712	4.147	-0.055	-3.428	9.158	-3.174	-15.52	21.68	-0.004	-13.23	-3.634
1996-2010	2.435	-0.331	-2.622	3.073	-0.164	-4.486	5.199	-1.815	-14.64	87.65	-0.367	-22.53	-2.676
MENA													
1983-1995	2.760	-0.401	-2.710	3.897	-0.070	-3.393	9.925	-3.080	-14.87	21.01	-0.023	-13.14	-3.574
1996-2010	2.435	-0.328	-2.616	2.989	-0.172	-4.883	5.236	-1.754	-18.70	87.25	-0.379	-25.95	-2.633
SSA													
1983-1995	2.757	-0.418	-2.674	2.859	-0.220	-3.982	8.003	-3.057	-10.68	76.51	-0.677	-17.55	-4.372
1996-2010	2.438	-0.355	-2.577	3.766	-0.158	-3.655	5.078	-1.860	-14.08	14.34	-0.331	-17.58	-2.705

Table C 2 Dynamic impact of the adverse real scenario in AEs grouped on the basis of their geographical areas

	t			t+1			t+2			t+3			cumulative median impact
	U	M	L	U	M	L	U	M	L	U	M	L	
Latin America													
1983-1995	2.144	-0.164	-2.052	1.903	-0.045	-1.676	9.695	-1.259	-16.29	21.53	-0.054	-14.65	-1.496
1996-2010	1.853	-0.112	-1.906	1.260	-0.066	-1.675	5.289	-0.414	-16.15	12.41	-0.240	-21.50	-0.715
Asia													
1983-1995	2.144	-0.167	-2.052	1.923	-0.030	-1.760	11.02	-1.283	-15.52	21.68	-0.004	-13.23	-1.483
1996-2010	1.850	-0.113	-1.908	1.339	-0.087	-1.754	5.498	-0.453	-14.64	87.65	-0.367	-22.52	-0.872
MENA													
1983-1995	2.147	-0.162	-2.048	1.902	-0.036	-1.783	11.46	-1.240	-14.87	21.00	-0.023	-13.15	-1.451
1996-2010	1.860	-0.110	-1.907	1.339	-0.088	-1.806	5.865	-0.454	-18.70	87.25	-0.379	-25.95	-0.872
SSA													
1983-1995	2.757	-0.418	-2.674	2.859	-0.220	-3.982	8.003	-3.057	-10.68	76.51	-0.677	-17.55	-4.372
1996-2010	2.438	-0.355	-2.577	3.766	-0.158	-3.655	5.078	-1.860	-14.08	14.34	-0.331	-17.58	-2.705

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