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Essay on Economic Cycles in Emerging and Advanced Countries: Synchronization, International Spillovers and the Decoupling Hypothesis

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To my family

*"La buona filosofia comincia col dubitare
e non finisce mai con l'ostinarsi"*

Ferdinando Galiani (from
Dialoghi sul commercio dei grani, 1770)

Abstract

This work aims to contribute towards the debate on “decoupling of Emerging Economies (EEs) from the Advanced Economies (AEs)” by addressing the following main questions: “Has the EEs’ vulnerability to external shocks (both real and credit shocks) coming from AEs changed over time? If so, has it grown or decreased, as the decoupling hypothesis claims?”

In order to measure the impact that external shocks would have on the EEs’ GDP growth in different periods of last decades, counterfactual experiments were performed using an econometric Time Varying Panel VAR model with factorized coefficients. The analyses show that over the last thirty years EEs have become less vulnerable to shocks spreading from the AEs. Despite this represents evidence in favour of the decoupling hypothesis, it is important to note that EEs’ resilience to external shocks has changed in a non-progressive manner over time, with phases of greater resilience followed by others of lower resilience, and vice versa; this outlines a “wave-like” path whose evidence has yet been fully analyzed in the economic literature.

Moreover, the EEs have shown to be more vulnerable to credit shocks than to real ones; this greater relative vulnerability has reached its peak in the most recent years.

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1. Introduction

1. Context, rational and objective of the study

Emerging markets countries also known as Emerging Economies (EEs) play an increasingly important role in the international economic scenario, with their contribution (together with Developing Economies [DEs]) to global economic production currently standing at 50.9% (compared with just 30% in the 1980s)[1]. From the economic point of view, their importance has grown in several respects: for example, they have become much more important in terms of direct foreign investment and portfolio investment, of the quantity of monetary reserves held, and in terms of their shares in international trade and financial transactions (Lane and Milesi-Ferretti, 2007). EEs' ratio of foreign trade to GDP – one of the most important indicators of a country's level of internationalization – rose from 30% in the 1980s to almost 80% by 2005; in particular, there was a significant increase in the share of intra-group trade for the EEs, that is between the emerging economies themselves, which rose from 9% of total foreign trade in 1960 to more than 40% in 2005 (Kose and Prasad, 2010).

Despite the relatively modest economic growth of Advanced Economies (AEs) between 2004 and 2007, the growth of EEs remained strong during that same period. This reinforced the idea known as the "decoupling hypothesis", whereby EEs have become less dependent on the economic trends of AEs. Advocates of this theory claim that its validity is based on the belief that together with the strengthening of the EEs' economic bases, the substantial development of real and financial connections between EEs may have reinforced intra-group economic ties, and in this way made such economies less vulnerable than before to the "fate" of AEs.

Nevertheless, following the recent financial crisis, the decoupling debate has partially changed direction: the emphasis has now partially shifted towards the idea that, as a result of globalization, all economies have become interconnected to a greater degree, which has inevitably caused stronger interdependency between the economic cycles of EEs and AEs.

Since the question has yet to be resolved (see Kose and Prased 2010, or Willet et al. 2011), either in terms of economic theory, where there is no univocal assessment on the decoupling hypothesis, or in empirical terms, I have tried to contribute towards the ongoing debate with this essay, also in view of the considerations set out below.

[1] International Monetary Fund, World Economic Outlook Database, April 2013.

The question of decoupling is not only interesting from a strictly academic point of view, but is also one that interests policymakers and economic operators owing to the important practical/operative implications that the phenomenon may have both when establishing national and international economic policy, and when defining corporate strategies concerning investment diversification and risk management.

It comes as no surprise to hear Christine Lagarde, Director of the International Monetary Fund, underline the importance of taking both national and global dimensions into account when establishing economic policy. In a recent speech (23rd August 2013)[2] she stated that: "We need to work better together to understand more fully the impact of these unconventional policies [the quantitative easing adopted by the Federal Reserve Bank to manage the recent financial crisis] – local and global –…"

Neither it is surprising to see major investment banks, such as Goldman Sachs and Morgan Stanley, among the major players popularizing the idea of decoupling. Jim O'Neill, head economist at Goldman Sachs, was one of the main advocates of the decoupling hypothesis, in fact the subject has been debated at length outside of academic circles as well.

Empirical analyses of decoupling have recently been performed by a number of scholars, many of whom have focused on the development over time of the degree of synchronization between the economic cycles of EEs and AEs. Writers such as Wälti (2012) and Yetman (2011a, 2011b), for example, have focused on the time path of the correlation between the main macroeconomic variables in EEs and AEs. Other writers, such as Kose et al. (2008, 2012) or Flood and Rose (2010), have firstly broken down each country's economic fluctuations into different components, namely the global component (common to all countries), the regional component (common to countries located in the same geographical area), the national component (country-specific), and what could be defined as the group component (common to countries with the same development level); then they have evaluated the decoupling phenomenon on the basis of the manner in which the global and the group components has varied over time. It should be pointed out that basically, as Helbling et al. (2007) stated, the breakdown of national economic cycles into the aforementioned components can be viewed as an equivalent approach to the correlation analysis because, for example, the global component is a measure of the extent of co-movement across national economic cycles of all countries.

[2] Speech on "The Global Calculus of Unconventional Monetary Policies". Downloaded from: http://www.imf.org/external/np/speeches/2013/082313.htm in August 25th 2013.

As Forbes and Rigobon (2002) have pointed out, the changes witnessed in the degree of synchronization of the economic cycles of different countries may be the result of two different forces. On the one hand, there are the structural elements which affect economic ties between different nations over the course of time; on the other hand there are changes in the nature of the shocks that may impact economies at different periods in history. This observation is extremely important since decoupling pertains to the way in which economic ties between advanced and emerging economies have changed over the course of time. It is a concept of structural importance regardless of the nature of the shocks that may affect an economy at various different stages in its history. Neither the analysis of correlation nor the breakdown of economic cycles enables us to distinguish the effects of the two forces during the course of synchronization (Willet et al. 2011); so despite their complexity and sophisticated methodologies, the aforementioned approaches may not be particularly suited to an analysis of decoupling. This is why I believe that the more appropriate approach is the one adopted by authors such as Guimarães – Filho et al. (2008) as well as Dees and Vansteenkiste (2007), who have tried to measure the impact of the USA's economic performance on the economies of given emerging nations. In particular, they have studied decoupling by comparing the repercussions that a shock in the USA would have had prior to, and after, the globalization era, on the economies of Asia's emerging nations (first paper) and on the emerging economies of Asia and Latin America (second paper).

This essay aims to contribute towards the debate on decoupling, by addressing the following questions.

Has the EEs' vulnerability to external shocks (that is, shocks outside of the EEs themselves) propagated by the AEs changed over the course of time? If so, has it grown, or has it indeed decreased as decoupling hypothesis claims? Are EEs more vulnerable to the real or credit shocks spreading from AEs?

With regard to the aforementioned literature, the spirit of the present study is best reflected in the approach adopted by Guimarães – Filho et al. (2008) or by Dees and Vansteenkiste (2007), and it aims to extend the empirical analysis of decoupling in various different directions.

First of all, it takes into consideration the "bank lending" variable too. The majority of empirical studies of decoupling focus on the Gross Domestic Product (GDP), as one of the principal indices of a country's economic performance or, for example, they consider a series of real indices such as industrial production, consumption and investment, and financial indices such as stock-market values. Bank lending has not been duly considered yet, despite the fact that it is widely believed (Kose and Prasad, 2010, Helbling et al, 2011) that lending can play a fundamental role in the economic dynamics of any country, and in the propagation of economic shocks from one country to another.

Secondly, unlike the prevailing literature, the present study does not consider the resilience of a small group of EEs to shocks spreading from the USA, but analyzes the sensitivity of a large number of EEs to the dynamics of a large number of AEs. Considering the multiplicity of economic relations between a large number of countries is of vital importance to any analysis of the decoupling phenomenon, since one of the arguments submitted by the advocates of this hypothesis is that the gradual strengthening of economic relations among EEs could have helped reinforced economic ties among such economies over the course of time, thus rendering them less vulnerable to shocks from the AEs than has been the case in the past.

Thirdly, unlike the aforementioned studies, the present work does not evaluate the time evolution of the EEs' vulnerability to external shocks by comparing two sub-periods chosen in a rather arbitrary fashion, in order to test for the existence of a "pre-decoupling" period and a "post-decoupling" period; instead, as it will be clear soon, this work assesses the EEs' vulnerability in a more flexible manner. Up until now decoupling theory has been empirically investigated by looking for some form of structural watershed, that is, a break in the coefficients of the econometric model identifiable at some point in the time (usually in the late 1980s, when according to many scholars, globalization[3] has become particularly evident). Such an approach is appropriate and effective if the object of study evolves discretely over time, namely as a break at certain point of time. However if a gradual evolution over time is plausible, as may well be true in the case of decoupling, then it would be more appropriate to utilize an approach (as in this work) allowing for a gradual change in coefficients over time rather than for an abrupt break.

In order to deal with the aforementioned questions, a Time Varying PANEL VAR with the factorization of the coefficients (Canova and Ciccarelli, 2004, 2009) has been utilized. This econometric instrument is particularly well suited to the pursuit of this study's objectives, for a number of different reasons.

The first reason is that the factorization of coefficients offers two immediate advantages: the first is that it significantly reduces the number of parameters that have to

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[3] Globalization is the process by which businesses or other organizations develop international influence or start operating on an international scale (Oxford Dictionary).

be estimated; this reduction is extremely important when handling a large-size PANEL model, as is the case in the present study. The second reason is that, depending on the factorization employed, the dynamics of the dependent variables may be interpreted as the result of various different components (as is the case in the work by Kose et al. 2008).

Secondly, the model used is particularly useful when investigating the international transmission of shocks from AEs to EEs since it duly takes account of the interdependency among countries; in other words, it allows for dynamic feedbacks across countries and variables. This feature renders analyses more realistic for the purposes of the evaluation of the EEs' responses to negative scenarios in the AEs.

Thirdly, as already said, decoupling may be a phenomenon that gradually evolves over time, rather than a structural break occurring at a given moment in time. Hence it could be more appropriate using a model with time varying coefficients, namely a model whose coefficients may change at each point in time, rather than remaining constant for a certain period and then changing, before remaining stable once again for a further period.

The empirical investigative approach adopted here consisted in two successive phases. Initially, some different model specifications were implemented, that is different factorizations of coefficients. For example, one comprised the global factor (i.e. the factor common to all countries) and the country-specific factor; another specification of the model added the group factor (the factor common to all the countries with the same level of economic development, that is the factor common to all emerging countries, the factor common to all developing countries, and the factor common to all advanced countries); a third specification extended the first by adding the regional factor (the one common to those countries belonging to the same geographical area, that is, North and Central America, Latin America, Asia, Europe, the Middle East and North Africa [MENA], Sub-Saharan Africa [SSA], and Oceania).

The specification best supported by the data, according to estimated marginal likelihood, was then used to perform experiments of counterfactual analyses (CAs); in particular, the experiments performed are the differences between two conditional expectations. In one case, the conditional expectation is the one the model would have obtained for the GDP of each country based on the hypothesis that the GDP growth rates of each advanced economy in the year of the simulated "shock" were lower than the actual GDP (namely the data observed at the time in which the shock is simulated). In the other case, the conditional expectation of GDP is the one the model would have obtained based on the actual GDP growth rate of each advanced economy. Note that these are one type of conditional forecasting exercises that, for example, Central Banks usually conduct in the assessment of current and future economic conditions.

These counterfactual experiments are designed to measure the impact a shock spreading from the AEs would have on the EEs' GDP. The intensity of the impact is an indicator of the vulnerability of the EEs to such external shock, and can thus be interpreted as an "indicator of the vulnerability" of the EEs. A lower impact suggests a lower vulnerability. These experiments were conducted for each year of the sample period, and so the "indicator of vulnerability" was calculated for each year in question. The results were then compared with one another in order to determine whether the EEs display a tendency towards lesser (or greater) vulnerability to negative scenarios in the AEs.

One of the main conclusions of this study is that the median results obtained from the simulations show that over the last thirty years, despite remaining sensitive to the effects of the shocks spreading from the AEs, emerging economies have nevertheless become less vulnerable to such external shocks, whether of a real or credit nature. One can say that the EEs are less vulnerable to external shocks from the AEs now than they were thirty years ago, however it is important to point out that their resilience to such shocks has changed in a non-progressive manner over the course of time, with phases of greater vulnerability being followed by phases of lower vulnerability, and vice versa. This "wave-like" dynamic, whose evidence has yet to be fully analyzed, may "upset" supporters of decoupling hypothesis, who on the contrary would have expected the economic strengthening of the EEs to have followed a progressive, and in a certain sense "monotonic increasing" pattern.

Another interesting finding is that during almost the entire period under examination, the EEs proved more relative vulnerability to external shocks of credit nature than to those of real nature. This greater relative vulnerability reached its peak in the latter years of the sample period, that is during the five years between 2006 and 2010.

2. Summary of the chapters

The essay is organized as follows.

The first chapter is entitled "The decoupling of Emerging Economies, a long-debated issue but still an open question. A survey". It aims to trace the debate on decoupling, presenting 1) the various interpretations of the phenomenon given in the literature; 2) details of how the prevailing opinion among academics and leading international observers has changed over the course of time; 3) the approaches followed in the empirical investigation, as well as their respective results and "strengths and weaknesses".

The second chapter is entitled "Is decoupling in action?". An attempt has been made here to utilize a broad selection of countries (112 in total). To this end, the focus has necessarily been placed on just one of the most important economic variables, that is, the rate of growth of GDP (at purchasing power parity per capita). Attention has thus been focused exclusively on the real economy. In this chapter, the empirical investigation strategy described above has been used to measure the evolution over time of the EEs' vulnerability to the adverse scenarios affecting the real economies of the advanced nations; moreover, following most of relative economic literature, I have also measured the degree of synchronization between the economic cycles of the advanced nations and those of the emerging nations, and between the advanced nations and those of the emerging nations divided into sub-groups on the basis of their respective geographical location.

The third chapter of the essay is entitled "International (spillovers in) macroeconomic-credit linkages and the decoupling phenomenon". This section offers an important addition to the empirical model, in the form of one of the most important financial variables, namely bank lending. The limited figures available for this variable has meant that the set of countries in question has had to be reduced in number, compared to that used in the previous section (from 112 countries to 73). Nevertheless, this section also provides an evaluation of the EEs' resilience to financial shocks (namely credit shocks) originating from the AEs, in addition to the real shocks (namely GDP shocks) from such countries. The addition of this financial variable has also enabled us to ascertain whether the emerging economies are more vulnerable to real shocks or to credit shocks.

2. The decoupling of Emerging Economies, a long-debated issue but still an open question. A survey

1. Introduction

Emerging economies (EEs) have progressively increased their role in the international economic scenario, to the point that the share in the global economy of EEs (together with Developing Economies [DEs]) has now reached 50.9% in 2013 (it was 30.9% in 1980)[4]. From an economic point of view, their importance has grown along different dimensional paths, as mirrored by foreign direct investments and portfolio investments, total currency reserves and, in more general terms, their shares in international commercial and financial trade. Technological innovation (e.g. more efficient means of transport or information communication technology), on the one hand, and policies encouraging commercial and financial trade (reduced customs duties or the setup of free trade areas), on the other, have lent significant support to integrating individual countries at global level (globalization). During the globalization period, for the EEs the trade openness[5] ratio rose from 30% to around 80% and more interestingly for the EEs the increase in international trade was accompanied by a significant rise in intragroup trading, which grew from 9% of total foreign trade in 1960 to over 40% in 2005 (Kose and Prasad, 2010).

With this growing importance of EEs, a fierce debate has begun as to whether the national economic cycles are converging or whether the cycles of EEs and advanced economies (AEs) are becoming disconnected, the so-called "decoupling of EEs from the AEs". The convergence argument is based on the idea that all economies have become more intertwined through trade and finance, which should make the national economic cycles more connected. In contrast, the decoupling argument is based on the idea that, together with the strengthening of EE's economic bases, the recent and prominent development of real and financial linkages among EEs may have reinforced the link

[4] Data refer to Gross domestic product based on Purchasing-Power-Parity (PPP) share of world total. The source is the International Monetary Fund, World Economic Outlook Database, April 2013.
[5] Trade openness is the ratio of total trade (export plus import) to GDP.

between emerging countries to the detriment of their relationships with the AEs which instead may have relatively weakened.

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-industry or inter-industry product specialization[6]. 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 inter-industry specialization, whereas the comovement is expected to increase when stronger trade linkages are associated with intra-industry specialization. The two types of industrial specialization are not mutually exclusive in a country, namely in some production sectors there may be inter-industry specialization and in some others there may be intra-industry specialization: comparative advantages encourage inter-industry specialization, and scale economies sustain intra-industry 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 in the countries.

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 facilitating inter-industry production specialization through the easy reallocation of capital, given the comparative advantage of each country. On the other side, contagion effects, transmitted through financial linkages, could increase synchronicity via cross-country spillovers of macroeconomic 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.

Many scholars investigated empirically the decoupling hypothesis, and in some cases provided different interpretations of this phenomenon. The decoupling implies a break in a relationship that was previously more coupled and closely linked. The concept

[6] Inter-industry trade is the exchange of totally different products between countries. Intra-industry trade is the two-way trade of products in the same industry classification. See Krugman (1981) for more details.

is not precisely defined so it allows for different readings. The basic idea is that the economic growth of one area becomes progressively less dependent on growth in another area (Rossi, 2009). This concept has been translated in two main different ways, indeed strictly connected to each other. Firstly, many authors speak on decoupling in terms of decreasing comovement of economic cycles and investigate it by computing correlation patterns between the economic cycles of variables of AEs and EEs looking for eventual decreasing correlation path (e.g. Wälti 2012), or investigate it by dividing the sources of a country's economic fluctuations into global, group (namely advanced and emerging economies groups) and national factors looking for eventual increasing importance of group factors in explaining country's economic fluctuations (e.g. Kose et al., 2008). Secondly, discussions on decoupling frequently proceed in terms of the extent of spillover of shocks from AEs to EEs (e.g. IMF, World Economic Outlook 2007).

From the empirical point of view, the investigation of the decoupling has been performed with different tools, namely different statistical and econometric instruments such as the correlation analysis or the VAR estimation, and with different set of data such a synthetic indicator like the gross domestic product (GDP) or a richer set of data like the industrial production, the export index and the unemployment rate for example.

Despite the different investigation techniques adopted to study it and the various way explored, the empirical literature has not yet reached a broadly accepted conclusion. As in the economic theory, also in the empirical economic literature there is still no prevalent opinion on the potential effects of international integration on the convergence or decoupling of EEs and AEs; hence in the academic the subject is still open to debate.

The question kindles not only the interest of academics. Also policymakers and practitioners are interested in the issue given the important practical implications that decoupling could have, for example, on the definition of national and international economic policies and on business strategies aimed at investment diversification and risk management.

Given the wide range of parties interested in this issue, its important implications and the absence of a broadly accepted conclusion, it is no wonder that the decoupling issue has been long debated. This survey aims to retrace the steps of this debate. In particular, it intends to present the different interpretations of the phenomenon discussed in the literature (section 2); the different predictions of economic theory on the issue of decoupling in the globalization era (section 3); how prevalent opinion among academics and leading international observers has changed historically, with the alternating prevalence of views in support and against decoupling (section 4); the approaches adopted in empiric investigation with their respective "strengths and weaknesses" and results (sections 5-8). Finally, section 9 presents the conclusions of this chapter.

2. Different interpretations and measures of decoupling

2.1 Interpretations

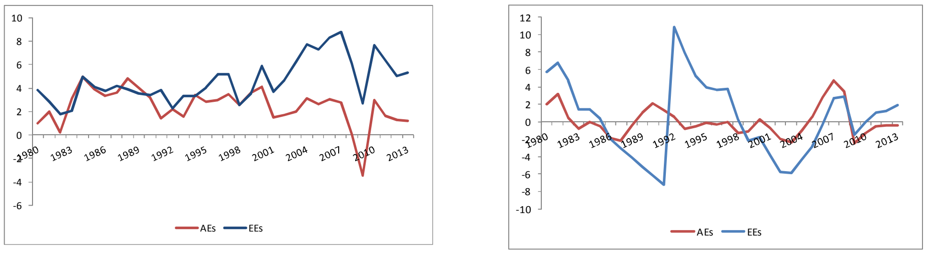
Decoupling of EEs from AEs implies a break in a relationship between the two groups of countries that was previously more coupled and closely linked. This definition is quite vague and so allows for different interpretations. Willett et al. (2011) argue that "… there are several different legitimate and useful concepts of decoupling and the key to productive discussion and analysis is to closely identify the type or types of decoupling that are being discussed [in the theoretical or empirical works], not to spend time in debate about what a specific concept of decoupling should be".

Perhaps there are two main simple reasons for the spread of the idea of decoupling among scholars, who then devised different readings of the phenomenon.

Firstly, a simple analysis of historical GDP dynamic in the various geographic areas, one of the variables most studied not only by academics but also by policymakers and leading international observers, suggests that the economic growth[7] of the advanced and emerging economies (Figure 2.1, panels 1 and 2), though similar up to 2001, seem to have differed more during the 2000-2010 decade; nonetheless a certain synchronicity of movement between the two variables has remained.

The second reason is that, though it is quite difficult to imagine that in an increasingly interconnected world the economy of one area can isolate itself from others, it cannot be excluded that the growing global interconnection could shift economic balances and change the economic dependencies between different areas as the concept of decoupling implies. In fact the idea that the economic growth of one area becomes progressively less dependent on growth in another area does not conflict with the phenomenon of globalization and, as illustrated in section 3 of this chapter, the economic

[7] Reference is made here both to the GDP growth rate and the deviation of GDP from its trend extracted by the HP (Hodrick-Prescott) filter (fully bearing in mind, however, the considerations made in following sub-section 2.1 on the possibility that the various trend extraction methods might not be equivalent).



1. % GDP annual growth rate

2. % deviation of GDP (at PPP) from Hodrick Prescott Trend. Own calculus on IMF data

Fig. 2.1 Economic Dynamic in AEs and EEs. Source: IMF.

theory leaves room for the possibility that globalization and decoupling could co-exist without conflicting.

Basically, the idea of the decoupling is that the economic growth of one area becomes progressively less dependent on growth in another area[8] (Rossi, 2009). As anticipated in the introduction of this chapter, this concept of decoupling has been translated in two main different ways, not mutually exclusive, but indeed strictly connected: 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.

With respect to the first point, many scholars used mainly two empirical investigation techniques which are different but basically equivalent. Firstly authors like Wälti (2012) computed correlation patterns between the growth of economic variables of AEs and EEs. Secondly, others authors (e.g. Kose et al., 2008) divided the sources of a country's economic fluctuations into global, group (namely advanced and emerging economies groups) and national factors, and stated the decoupling in terms of gradually increasing importance of group factors in explaining those fluctuations. Note that, this second way of interpreting decoupling is strictly linked to the first because breaking down national economic cycles can be seen as a different method for quantifying synchronization across countries; in fact the contribution of the global factor is a measure of the extent of comovement across national business cycles of all the countries, and the

[8] Let me note that this reading of decoupling is implied by a more "extreme" concept which refers to decoupling as the notion that one area becomes a self-contained economic entity with potential for maintaining its own economic growth trend regardless of the economic trend of another area. This stance is quite extreme because decoupling is viewed as referring to almost complete regional insulation. It became a popular theme mainly in Asian policy circles in the first years of the 2000s when, despite the 2001 recession and the tepid economic growth of advanced economies from 2004 to 2007, the growth of India and China remained strong during that same period (Athukorala and Kohpaiboon, 2009); nevertheless it did not received significant consideration in the economic literature.

group factor is a measure of the extent of comovement across national business cycles of countries belonging to the same group, as highlighted by Helbling et al. (2007).

With respect to the second point, discussions on decoupling frequently proceed in terms of the extent of spillover of shocks from AEs to EEs (e.g. IMF, World Economic Outlook 2007).

2.2 Measures

In general, any concept (decoupling is not an exception) needs to be translated or associated with data in order to perform empirical investigations or for operational purposes. So the question is how to measure the decoupling phenomenon.

The Gross Domestic Product (GDP), despite the well-known criticism on the capacity of this variable to represent the real economic status of a country, is probably one of the economic indicators that best summarizes the economic activity of a country, in fact most literature on decoupling has focused on the GDP data. On the other side, some papers did take into account a more extensive set of variables such as the industrial production index, consumer price index or current accounts, for example, to have a more detailed picture of a country's economy[9]. However, over and above the variable (or set of variables) considered, what actually makes the various contributions to the literature profoundly different is not so much the type of variable observed but how it is processed to extract the country's economic trend and the country's economic cycle.

In effect, using a set of indicators such as industrial production, export and unemployment or a synthetic indicator such as GDP to measure the fundamental characteristics of a country's economy is essentially equivalent, disregarding the greater or lesser detail level relating for example to the timing of turning points of the economic cycle if the synthetic indicator and set of indicators have different time frequencies (for example quarterly, monthly, etc.). Obviously the information like the exact timing of the economic cycle is a very important one but separating economic trend from economic cyclical is even a more delicate aspect. Economists like Marshall, Edgeworth and Keynes often stressed the distinctions between long term (which refers to economic trend) and short term (which refers to economic cycle), but despite the importance of these concepts, there is no unanimity on the way in which the two components of the economic dynamic, namely trend and cycle, should be handled when investigating the decoupling phenomenon.

[9] One advantage of using indicators other than GDP could be, for example, the greater availability of information resulting from the higher frequency of data publication.

An extensive part of literature (e.g. Kose et al., 2008) focuses on the short-term growth rate of real GDP (year on year, for example) to extract economic cycle from the time series. Another part of literature (e.g. Wälti, 2012) makes recourse to more sophisticated methods to detrend the time series and separate the cyclical component from the trend component. The literature indicates several ways of doing this, such as the Hodrick-Prescott filter, the Baxter-King filter or the assumption of a quadratic trend for example. As Canova explained (1998), it can happen that the different methods lead to widely differing results, and therefore there are also contributions in the literature (e.g. Flood and Rose, 2010) that instead of using a single method use several to assess the reliability of their results from one method compared to another.

When comparing the economic dynamics of advanced countries against those of emerging countries, the method with which the cycle and trend components are handled must be taken into great consideration because the two components have very important and different roles in determining the overall economic dynamics of the two country types. As documented in Aguiar and Gopinath (2007) emerging markets, unlike developed markets, are characterized by frequent regime switches, owing to the dramatic reversals in fiscal, monetary and trade policies observed in these economies, and consequently "... shocks to trend growth are the primary source of fluctuations in these markets [emerging markets] as opposed to transitory fluctuations around the trend. On the other hand, developed markets are characterized by a relatively stable trend.". So ignoring the fact that there are different ways to treat the two components of economic dynamic could be misleading when the results of different papers, which used different methods, are compared.

In addition to the type of method used to extract economic trends and cycles from time series, another important element to be taken into account in the study of decoupling is the demographic dynamic. As was outlined by Reinhart and Rogoff (2012), the impact of population growth on GDP growth is an important consideration when working with historical series. Considering only the GDP growth rates and ignoring the demographic dynamics can be misleading when the population growth rate is high and unstable, as is the case of many EEs in which the high birth-rate, from one hand, and the significant emigration phenomenon, from the other, make complex the demographic phenomenon.

Perhaps, as for the interpretations of the decoupling, there are also several different legitimate and useful ways to measure it, and what is really important to productive discussion is to identify the measure that is being discussed, not to spend time in debate about what a specific way to measure it should be.

3. Decoupling and globalization: could they coexist?

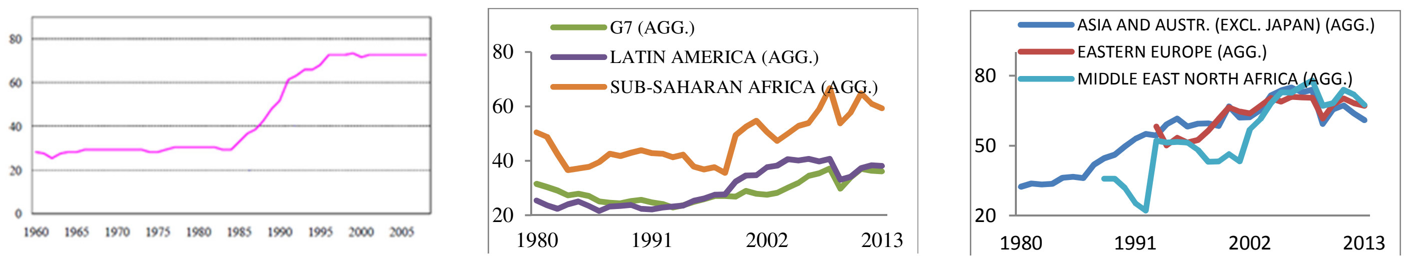
This section will first describe the key stylized facts on the economic integration between different geographic areas (globalization). Further on, it will attempt to illustrate how the economic theory leaves room for the possibility that the concepts of globalization and decoupling can coexist without necessarily conflicting.

3.1 Increasing international trade linkages

In recent decades economies have become more integrated with respect to many different dimensions[10], not only economic but also, for example, the cultural dimension.

The volume and nature of international trade linkages have changed drastically as result of various forces. Transport and communication costs have been an important factor. Air shipping costs have declined over time, and costs of ocean shipping have come down due to containerization and other technological efficiencies (Hummels, 2007). Further important factors have been policies to improve the liberalization of international trade, such as the lowering of trade barriers and the reduction of tariffs, or other means of restraining international trade, that were implemented in particular after the breakup of the Soviet Union.

Figure 2.2 panel 1, based on the papers of Sach and Warner (1995) and Wacziarg and Welch (2008), shows the fraction of countries with a fully liberalized trade regime,



1. Trade liberalization

2. Trade to GDP ratio (%)

3. Trade to GDP ratio (%)

Fig. 2.2 Trade openness. Sourses: Kose and Prasad (2010) on data of Sachs and Warmer (1995) and Waczing and Welch (2008), and own calculus on EIU data.

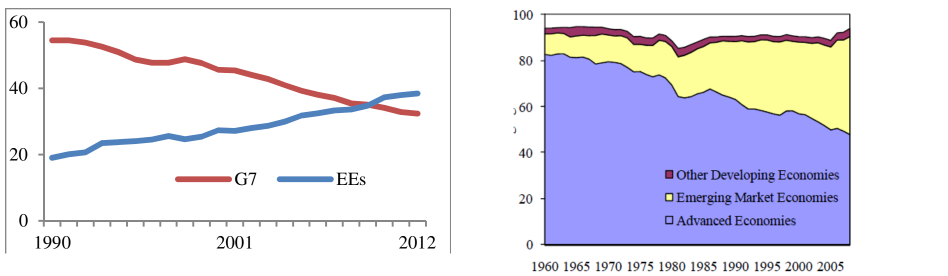
[10] See, for example, Kose and Prasad (2010) for an extensive description of the time path of trade and financial linkages between countries and groups of countries.

and as can be seen, trade liberalization has increased sharply from 1986 onwards (during the globalization period).

Lower costs and stronger policies supporting international trade have encouraged the intensification of international commercial trade, with its share of GDP gradually increasing in all the main geographic areas, as illustrated in Figure 2.2 panels 2 and 3. The Figure shows the evolution of the ratio of total trade to GDP separately for six groups of countries (G7 economies, Latin American EEs, Sub Saharan Africa EEs, Asian EEs, Eastern Europe EEs and Middle East and North Africa [MENA] EEs). In particular, until 1985, trade openness was relatively stable for G7, Latin America and Sub Saharan Africa, and it increased significantly during the globalization period; while for the other groups the straitening of the openness ratios was significant also before 1985.

In Figure 2.3, panel 1 shows the distribution of global export percentages among the two groups of countries (G7 and emerging economies). Whilst the share attributed to G7 economies is still very high, it gradually reduced from around 70% in the 1990s to 35% in 2012. At the same time, the percentage of global export attributable to emerging economies grew from 20% in 1990 to 40% in 2012. The different distribution of global export flows also reflects a different distribution of the trading flows of the two groups of countries. In particular, for emerging economies the share of trade with advanced economies has remained significant, but gradually reduced over the years from around 80% of total EEs foreign trade in 1960 to 50% in 2005, whilst in the same period the percentage of intragroup trade rose from 9% to 40% (see Figure 2.3 panel 2).

Information about production opportunities in foreign countries has become easier to obtain, for example stronger availability of information through the Internet (world wild web), or for example promoted by immigrants[11] and multinational companies



1. % share of world good exports; own calculus on EIU data

2. Share of EEs trade by group partners; source Kose et al. 2010

Fig. 2.3 World trade. Sources: own calculus on EIU data and Kose and Prasad (2010).

[11] In 2007, an estimated $240 billion in remittances went to developing countries, more than double the flow in 2001 (Federal Reserve Bank of Atlanta, 2008 conference "Remittances and the Macroeconomy," February 21-22).

facilitating networking (see Kohn, 2008). These factors may have supported the expansion of trade in manufactured goods. Figure 2.4 from panel 1 to 6 shows the composition of trade by group of countries from 1960 to 2007. While the average share of advanced economies' exports accounted for by manufacturing exports rose slightly and remained the highest in the full sample period (see panel 1), for both emerging economies and developing economies the share of manufacturing exports rose strongly and, for example, became the most important part of exports (see panels 2 and 3).

These changes in the share of manufacturing exports reflect changes in inter-industry and intra-industry trade. Intra-industry trade, measured by the average bilateral Grubel-Lloyd index, has been increasing between Emerging economies and G-7 countries since 1970, although with regional peculiarities. For G-7 countries and Asia the intra-industry trade increased with higher intensity than others regions (Akin and Kose, 2008), and for the countries that joined the EU in 2004, despite the share of intra-industry trade has been increasing in recent years, the inter-industry trade still accounts for almost 50% of the total trade (Kawecka-Wyrzykowska, 2010).

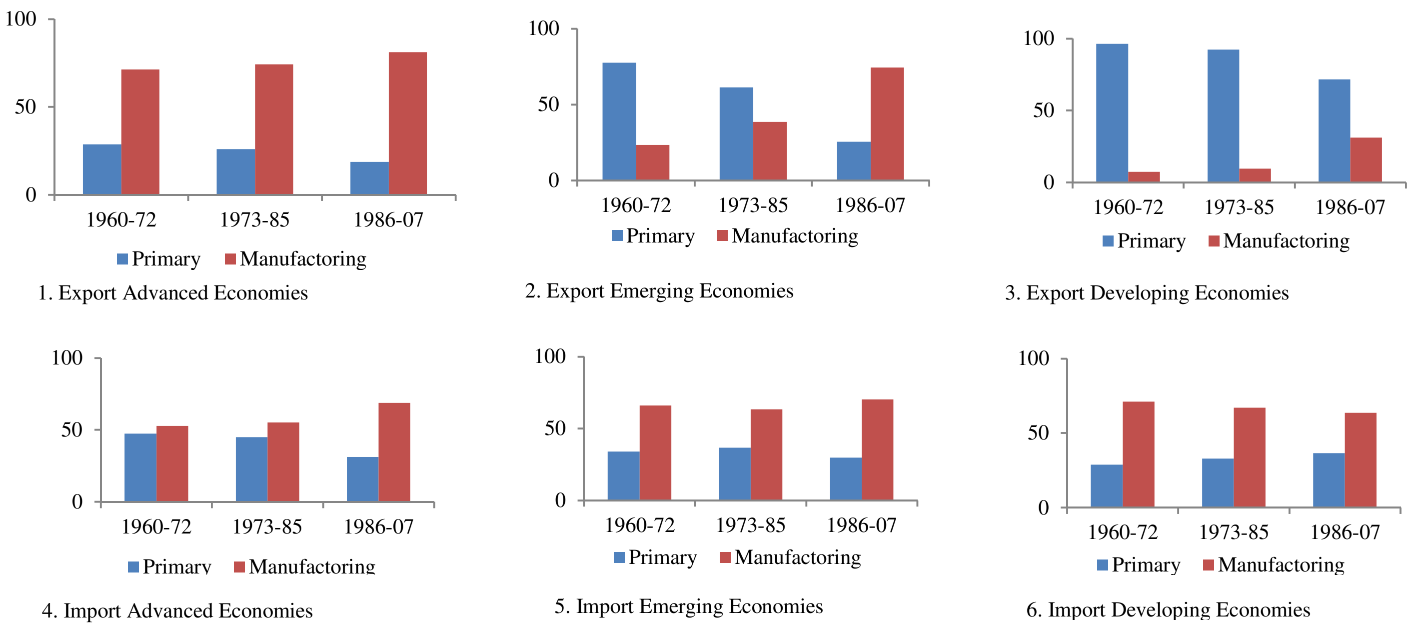


Fig. 2.4 Composition of international trade. Source: own calculus on Kose and Prasad (2010) data.

3.2 Increasing international financial linkages

Another area of impressive growth in international linkages has been in financial activities. The strong increase of financial linkages was mainly associated with the rapid liberalization of financial regimes after the mid-1980s. Figure 2.5 panel 1, based on the papers of Bakaert et al. (2006), shows the fraction of countries with a liberalized financial systems. As can be seen, financial liberalization increased sharply in the globalization period. Many structural changes improving the degree of liberalization of financial systems took place among emerging economies. For example the privatization of state-owned enterprises, or the liberalization of domestic banking systems and stock markets, the removal of restrictions on the acquisition of assets by foreigners (see Lane and Milesi Ferretti, 2007).

Following Lane and Milesi Ferretti, the level of financial integration of country groups can be calculated as the sum of gross international financial assets and liabilities[12]. These indicators, interpretable as financial openness indicators, are plotted in Figure 2.5 from panel 2 to 4 for the AEs, EEs and DEs. The Figure shows that financial openness increased for all three groups of countries during the globalization period.

The financial integration has occurred globally, however its evolution has been uneven. Integration in industrialized countries measured by the ratio of the sum of their foreign assets and liabilities to GDP has tripled since 1990, while an analogous measurement for emerging and developing economies shows an increase of about 50 percent (Lane and Milesi Ferretti, 2007).

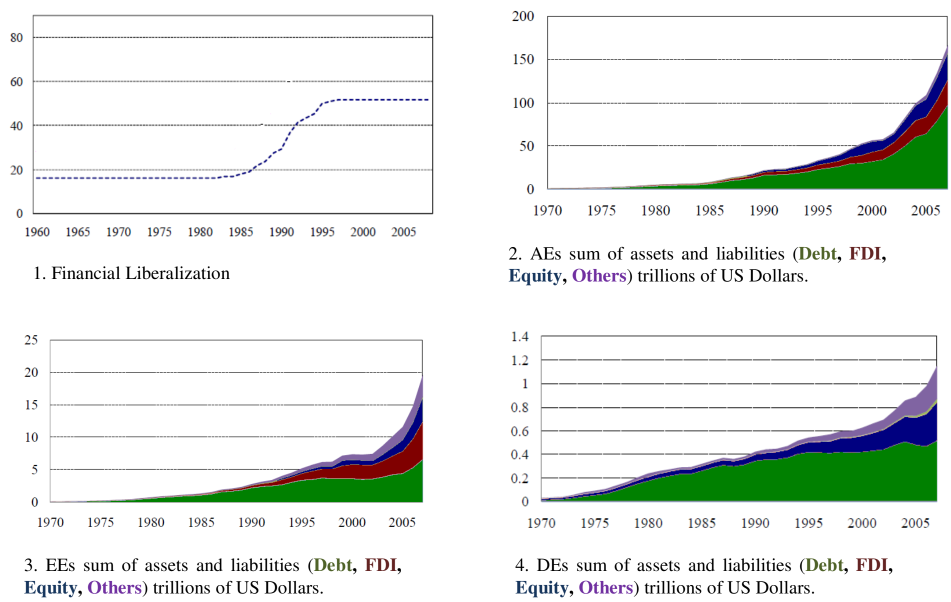


Fig. 2.5 Financial openness. Source: Kose et al. (2010).

[12] The total assets and liabilities contains debt, foreign direct investment (FDI), equity, financial derivatives and total reserves.

3.3 Decoupling and increasing international linkages: what does theory say?

Does economic integration between different countries preclude the option of decoupling? In theory, as will be illustrated in this sub-section, the growing international integration could either favour or counter decoupling.

Theoretical models make different predictions about the effects of trade integration on comovement among national economic cycles.

International trade linkages represent the way through which both supply-side and demand-side spillovers can spread across countries. These spillovers can increase the degree of business cycle comovement. For example, boosting consumption in one country can generate increased demand for imports, reinforcing economies abroad.

However, the stronger trade linkages can be associated to stronger intra- or inter-industry trade, namely an increase of international trade can be associated to an increase in intra- or inter-industry specialization. The way in which the increased specialization affects the degree of comovement in national economic cycles depend on the nature of specialization (Frankel and Rose 1998). More precisely, if 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 inter-industry specialization, whereas comovement is expected to increase when stronger trade linkages are associated with intra-industry specialization. The two types of industrial specialization are not mutually exclusive in a country: for some country's production sectors the comparative advantages encourage inter-industry specialization, and for some others the scale economies sustain intra-industry specialization. Thus, in theory, the effect of production specialization on the degree of comovement in economic cycles is not univocal but depends on which type of production specialization prevails in the country.

There is also no univocal theoretical prediction about the effects of financial integration on the comovement of national economic cycles. As explained in depth by Kose and Prasad (2010), financial integration could decrease the synchronicity of economic cycles facilitating inter-industry production specialization through the easy reallocation of capital, given the comparative advantage of each country. On the other hand, contagion effects and shocks transmitted through financial linkages could increase synchronicity via cross-country spillover of macroeconomic fluctuations (Classens and Forbes, 2001). 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 (Lewis 1999 and Van Wincoop 1999).

Foreign direct investment flows could be the way that knowledge and productivity shocks spread from one country to others and so, as explained in Kose et al. (2009), foreign direct investments may increase the comovement of economic cycles.

According to some authors, communication technology may play an important role in driving the economic cycle fluctuations (Cochrane, 1994). Faster and more accurate dissemination of news[13] may have a positive impact on the synchronization of economic cycles in the case, for example, good news on the economic perspectives of a country increase domestic demand and also raise the consumer demand of other countries holding stocks in the country to which the good news refers.

Macroeconomic policies could act in favour of increasing synchronicity of business cycles across countries, but they could also generate decreasing synchronicity.

On the one hand, increased economic integration could affect the synchronization of economic cycles by conditioning the way in which macroeconomic policies are implemented in the different countries, namely the stronger economic linkages may lead to a higher degree of policy coordination. This could have a positive impact on the comovement of economic cycles because it could increase the correlation between shocks associated with country-specific policies. This point has been debated by many authors such as Darvas et al. (2005), Flood and Rose (2010), Crucini et al. (2008).

On the other hand, macroeconomic policies can also lead to lower synchronization of economic cycles. More disciplined fiscal policies and more credible monetary policies could act as shock absorbers against external shocks (Rose, 2007 and Ghosh et al., 2009). For example, prudent fiscal policies with a low level of public debt and deficit could create room to contrast external adverse shocks by implementing strong countercyclical fiscal policies.

4. The long-debated issue: a brief historical excursus

The decoupling has been long debated in both academic and non-academic spheres. This is not surprising because, as already seen, from one hand the economic theory (and also the empirical investigation, as will be seen in-depth later on) fails to

[13] Jaimovich and Rebelo (2008) analyze the effects of news about future productivity on business cycles in a small open economy model.

provide a single key to reading the issue of decoupling, but rather indicates an array of potential effects of stronger international integration on the level of comovement and interdependence of economic cycles; from the other hand, the decoupling has considerable practical implications on the country's economic policy and on the corporate strategies. Knowing whether fluctuations in the AEs and EEs are similar, understanding their sources and characterizing their time-related variations is important for both policymakers and managers.

If variations in economic activity in countries with different institutions, economic structures or economic policies are driven by a common cause then international policies, or national policy coordinated at international level are (more than national policies alone) the key way to manage national economic activity. Moreover, knowing whether and to what extent the economic dependence between different groups of countries has been affected by increasing international linkages is crucial because structural time variations may weaken the usefulness of policies that may have been effective in the past[14]. For example the IMF Director, Christine Lagarde, said "We need to work better together to understand more fully the impact of these unconventional policies [the quantitative easing adopted by the Federal Reserve Bank to manage the recent financial crisis] local and global…" (speech of 23 August 2013).

As regards industrial strategies, accepting or rejecting the idea of decoupling has wide-ranging implications because it affects the potential profit margins and risk management of a business as it determines a range of possible optimal allocations of resources and has an impact on investment diversification. Therefore, it is no wonder that major investment banks such as Goldman Sachs and Morgan Stanley have been among the key players in discussing the idea of decoupling. Jim O'Neill[15], chief economist of Goldman Sachs, was one of the main advocates of the decoupling idea, and Keith Fitz-Gerald, the investment director for Money Morning, wrote a book in 2010 entitled "Fiscal Hangover: How to Profit from the New Global Economy", a broad section of which is dedicated to the decoupling issue.

The issue of decoupling has always kindled a great deal of interest and, as described by Willet et al. (2011), its debate has historically been characterized by

[14] The importance of decoupling in the definition of economic policies clearly emerges from analysis of the many reports by leading international institutions, e.g. the IMF (World Economic Outlook, April 2002, April 2007, October 2012), the European Bank for Reconstruction and Development (Transition Report 2009) and the Asian Development Bank (Asian Development Outlook 2009, 2010).

[15] Known for coining the acronym "BRIC" for the world's biggest emerging markets of Brazil, Russia, India and China in 2001.

alternation between supporters and opponents. Early talks on decoupling took place in the 1980s, in Asia, on the basis of a strong domestic demand and consumer confidence in the region. However, in 1997-1998 with the explosion of the Asian financial crises the concept of decoupling fell into oblivion. The decoupling thesis come back as a popular theme in Asian policy circles (Athukorala and Kohpaiboon, 2009) in 2001 when the US and Europe first went into recession and later, from 2002 to 2007, saw a relatively tepid economic growth, while the growth of emerging economies remained strong during that same period.

The idea of decoupling still continued to be supported in 2007, even after the slowdown of the U.S. economy and the first signs of the U.S. subprime crisis. The IMF report "World Economic Outlook, April 2007" says "Overall, these factors suggest that most countries should be in a position to 'decouple' from the U.S. economy and sustain strong growth if the U.S. slowdown remains as moderate as expected." (IMF, 2007). At that time, the decoupling idea was not only supported by economists from a number of important international institutions, but also by practitioners. Big investment firms like Goldman Sachs believed "China, together with emerging Asia, stands a very good chance of outperforming and decoupling from the US economy in the coming few years." (Asian Economics Flash, 2007).

2008 was the year when prevailing opinion swung away from decoupling. With the Lehman Brothers' crash, the financial crisis affected the real economy and spilled over to the rest of the world, also sweeping emerging economies into its wake. Doubts about the validity of decoupling also found their way into the minds of those who previously had been its strongest supporters. In 2008 Goldman Sachs mitigated the extent of arguments in favour of decoupling by emphasizing that it was difficult to ignore the slowdown in the US economy for most of the rest of the world (O'Neill, 2008).

The swings between "ayes" and "nays" for decoupling have not stopped, however. Even in 2009, when the main advanced economies like Europe and the US continued to show signs of economic weakness while China and India quickly rebounded, the decoupling thesis returned as crucial topic. In its World Economic Outlook of October 2009, the IMF pointed out that emerging economies like India and China would lead the world economic expansion that year, growing at rates of 5.4% and 8.5%, respectively. El-Erian (2009) wrote "Given the pick-up in economic activities of some emerging economies and the fact that equity valuations are now back above the pre-Lehman levels, the decoupling argument is again gaining consensus today".

5. Synchronization of economic cycles between AEs and EEs

As is now common practice in literature (see e.g. Frankel and Rose, 1998, Rose and Engel, 2002, Kose et al., 2003, Imbs, 2004, 2006, Baxter and Kouparitsas, 2005, Fidrmuc and Korhonen, 2006), the economic cycle synchronization is usually measured using the Pearson correlation coefficient between output growth (usually measured by GDP growth) of two countries[16] as follows:

$$\rho_{ij} = \frac{\sum_{t=1}^{T}\left((G_i(t)-\overline{G_i})(G_j(t)-\overline{G_j})\right)}{\sqrt{\sum_{t=1}^{T}(G_i(t)-\overline{G_i})^2}\sqrt{\sum_{t=1}^{T}(G_j(t)-\overline{G_j})^2}} \quad (2.1)$$

where $G_i(t)$ is the output growth rate of the country i at time t and $\overline{G_i}$ is the arithmetic mean of the output growth rate over the period $t = 1,2,3,\dots T$; and mutatis mutandis for $G_j(t)$ and $\overline{G_j}$.

In Kose et al. (2003b), the authors perform an empirical investigation based on annual data over the period 1960–1999 for real growth of GDP per capita and real growth of per capita consumption, using a sample of 76 countries: 21 industrial and 55 emerging and developing. They compute the correlation coefficients of the growth rates of the two variables in each country with the growth rates of the corresponding world variables[17]. They find that, for emerging and developing countries the correlations are in general decline in the 1990's, thus, during the most recent period of globalization, there is some evidence that on average business-cycle comovements have become less synchronized[18].

Whilst the results presented in Kose et al. (2003b) support decoupling, those reported by Flood and Rose (2010) are against it. Flood and Rose computed correlation coefficients over five-year rolling sub-samples of quarterly GDP data from 1974 to 2008 of 64 countries (21 developed economies and 43 emerging economies). In addition to considering the annual GDP growth rate, the authors also performed their investigation on detrended data using other methods: the Hodrick-Prescott filter, the Baxter-King filter

[16] Or more countries by averaging the correlation coefficients between pairs of countries.

[17] The PPP-weighted aggregates (Purchasing Power Parity) of GDP and consumption in G-7 countries were used as the measure of world variables.

[18] To further study and understand the change in the degree of synchronization, the authors also perform a regression analysis of the factors that influence correlations of each country's macroeconomic variable with the corresponding world variable. For the output variable, their results are essentially in line with those of some other studies, e.g. as per Imbs (2004), and highlight the importance of trade and financial linkages in accounting for economic cycle comovement among emerging economies and the world economy. For consumption the results are weaker and only trade linkages appear to have a positive effect on cross-country movements in consumption.

and the assumption of linear and quadratic trends. The data have been used to compute correlation coefficients between pairs of countries in which one country is industrial and the other is emerging. The main finding is that the average level of economic cycle synchronicity (the correlation coefficient) varies somewhat over time, but is typically at a level of 0.25 or thereabouts. There is no evidence that the average correlation coefficient is significantly lower towards the end of the sample period. Hence, there is no evidence in favour of decoupling. The conclusion is the same if only the synchronicity between emerging countries and the G-7 aggregate[19] is considered.

An important aspect considered by Kose et al., but disregarded by Flood and Rose, was the demographic dynamic. As mentioned in section 2.2, GDP growth can be misleading when the population growth rate changes significantly, as is the case in many emerging economies. Therefore using the GDP per capita, as did Kose et al., is more appropriate in cross time and cross country analyses.

On the other hand, however, compared to that of Kose et al., Flood and Rose's analysis – albeit on a more limited set of countries – takes more account of the problem relating to breaking down the economic dynamic of countries into two components: trend and cycle. In fact, unlike Kose et al., Flood and Rose assess the reliability of their results against the different methods for detrending time series[20].

Although it is common practice in literature to measure economic growth synchronization by computing the correlation coefficient between the economic variables of two countries, or a group of countries, the correlation's ability to describe the economic cycle synchronization is subject to three important critiques: 1) the use of correlation coefficients over rolling sub-samples of data is problematic in identifying a structural break in the degree of business cycle synchronization (see Wälti, 2012); 2) the correlation coefficient can be counter-intuitive in its treatment of data (see Yetman

[19] The PPP-weighted aggregates of GDP in G-7 countries were used as the measure aggregate variable.

[20] An investigation on the decoupling hypothesis with a special emphasis on the distinction between trend and cycle is presented in Dilip and Dubey (2013). The authors used two heavily data-intensive frequency domain methods: causality testing in the frequency domain and wavelet correlations . They needed to use a highly frequently available measure of output, so the authors employed the industrial production index on which data is generally available monthly. Their focus was on 7 Asian emerging economies and, for both methods the conclusion offered strong evidence in favor of decoupling. As stated in Dilip and Dubey, frequency domain causation was suggested in the seminal paper by Granger (1969) and later extended by Geweke (1982, 1984), and the properties of wavelets are discussed in Percival and Walden (2000). See Dilip and Dubey for an overview of the two methods.

2011a); 3) the correlation coefficient may be biased due to heteroskedasticity of the time series (see Forbes and Rigobon, 2002, and Willett et al. 2011).

5.1 First critique: problem in identifying structural breaks using correlation coefficients over rolling sub-samples of data

With respect to the first critique, as explained in Wälti (2012), by using rolling sub-samples of data it can happen, for example, that the last estimated correlation coefficient is calculated using the last five years of data. In this case, if the degree of business cycle interdependence changes around the end of the last time window, the correlation coefficient may not catch it. Moreover, in general, the choice of windows can be quite arbitrary and different time windows for the same data set can return different results[21].

To overcome this problem, Wälti proposed an innovative measure of economic cycle synchronization which can be computed at each point of time (for example, each year in the case of yearly data) and expresses the same qualitative information as the correlation coefficient. The advantage of this innovative indicator is that, as it can be calculated at each point of time, it allows for proper identification of structural breaks even if they occur at the end of the sample period.

Wälti started from the fact that the Euclidean distance between two standardized random variables conveys the same information as the correlation coefficient[22]. Hence he proposed measuring the synchronization between the economic cycles of countries i and j by

$$\varphi_{ij}(t) = \left|g_i(t) - g_j(t)\right| \tag{2.2}$$

where $g_i(t)$ and $g_j(t)$ are, respectively, the standardized[23] economic growth at time t of the country i and the country j. If $\varphi_{ij}(t)$ is equal to zero, it means that at time t the economies of the countries i and j are perfectly synchronized. Any positive value means less than perfect synchronization; the larger the value of the Euclidean distance indicator, the less synchronized the countries are.

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[21] For example, this is the case of Artis and Zhang (1997, 1999) and Inklaar and de Haan (2001). They used the same data, different time windows and reached the opposite conclusion about the relationship between the economic cycle synchronization.

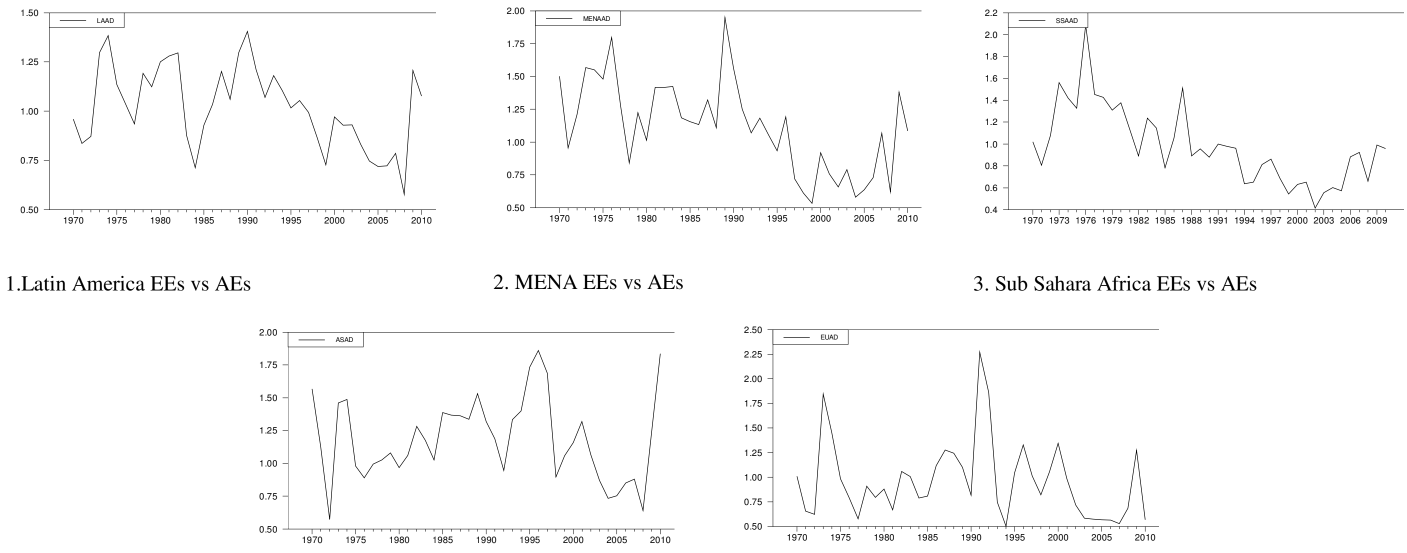
[22] See Wälti (2012) for a detailed description of the indicator.

[23] $g_i(t) = \frac{(G_i(t)-\overline{G_i})}{\sqrt{(1/(T-1))\sum_{t=1}^{T}(G_i(t)-\overline{G_i})^2}}$ where $\mathrm{G_i(t)}$ is the output growth rate of the country i at time t and $\overline{G_i}$ is the arithmetic mean of the output growth rate over the period $\mathrm{t} = 1,2,3, \ldots \mathrm{T}$.

Wälti based his empirical investigation on a dataset ranging from 1980 to 2008 and covering 56 countries, of which 30 emerging economies[24] and 26 advanced economies. He focused on detrended data of the GDP, in particular on the "output gap", namely the percent deviation of actual GDP from the trend GDP[25]. The output gap of each country was standardized by subtracting the mean and dividing by its standard deviation. In this way for each country i $(i = 1,2,3, \dots 56)$ he computed the quantity $g_i(t)$ used in equation (2.2).

The author concluded that there has been no decoupling in recent years because the average degree of business cycle synchronization between the business cycles of the 30 emerging markets and the business cycles of the 26 advanced economies has increased during the last decade. This result was robust both in relation to the different filters applied to extract the trend from the original time series and to the different grouping of emerging economies (Asian, Latin American and Eastern European emerging countries).

Wälti's work did not take "population trends" into account. However, as can be seen in Figure 2.6 (panels from 1 to 5), if the same method is applied to per capita GDP, albeit on a broader sample (112 countries of which 23 advanced, 59 emerging and 30



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. 2.6 Euclidean distance computed on deviation cycles. Own calculus on Penn World Table 7.1 data.

[24] The emerging market countries come from different regions of the world: 8 Asian economies, 9 Latin American countries and 13 Eastern European economies.

[25] Wälti explored three different alternative filters (Hodrick-Prescott, Baxter-King, Christiano-Fitzgerald) to extract the trend from the original data.

developing) and the years 2009 and 2010 are also included, the main conclusions drawn by Wälti remain unchanged. Nevertheless it seems that with the escalation of the worst financial crisis of the last 40 years, the indicator jumped to historic highs in 2009, indicating a low degree of correlation between economic cycles. However, in some cases, for examplefor the MENA or Europe emerging economies, this movement of the indicator was temporary and by early 2010 the indicator returned under the average of the last 20 years.

5.2 Second critique: the correlation coefficient may be counter-intuitive in its treatment of data

With respect to the second critique, as explained in Yetman (2011a), the correlation coefficient may be counter-intuitive. To overcame this critic, Yetman (2011a) proposes an indicator which, as will be shown in this section, is equivalent to the Wälti 's indicator described in the above sub-section 5.1.

Following Yetman (2011a, 2011b), the Pearson correlation can be broken down into its period-by-period contributions.

Consider the quantity

$$g_i(t) = \frac{(G_i(t) - \overline{G_i})}{\sqrt{(1/(T-1))\sum_{t=1}^{T}(G_i(t) - \overline{G_i})^2}} \tag{2.3}$$

which is the same quantity used in equation (2.2) for country i. Let compute also $g_j(t)$. The product

$$\rho_{ij}(t) = g_i(t)g_j(t) \tag{2.4}$$

is interpretable as a measure of the comovement between countries i and j at time t and, up to degrees of freedom correction, the average of these measure equals the Pearson correlation coefficient[26] of equation (2.1), namely

$$\frac{1}{T}\sum_{t=1}^{T}\rho_{ij}(t) = \frac{T-1}{T}\rho_{ij} \tag{2.5}$$

At this point, Yetman easily shows that the correlation coefficient is counter-intuitive in its treatment of data. Consider, for example, the case in which $\rho_{ij}(t)$ is equal to zero. $\rho_{ij}(t) = 0$ means that data at time t suggest a complete decoupling between countries i and j and in fact, as can be seen from equation (2.5), it is zero the contribution to the

[26] See Yetman (2011a, 2011b) for more details.

correlation coefficient ρ_{ij} coming from data at time t. The point is that there are different cases in which $\rho_{ij}(t)$ can be zero, and they give very different information on the synchronization but, even so, the contribution to the correlation coefficient is the same (namely zero).

More precisely, there are three possible cases:

1. $G_i(t) = \overline{G_i}$ and $G_j(t) \neq \overline{G_j}$;
2. $G_i(t) \neq \overline{G_i}$ and $G_j(t) = \overline{G_j}$;
3. $G_i(t) = \overline{G_i}$ and $G_j(t) = \overline{G_j}$

While the first and second cases are more consistent with the decoupling idea because average growth in one country occurs simultaneously with deviation from average growth in the other, the third case is more consistent with a strong synchronicity owing to both economies growing at the respective average rate.

Hence, the Pearson correlation coefficient is an indicator which can process data in a way not fully appropriate to the ultimate aim of analyzing the economic synchronicity between countries.

To overcome this critique, instead of the Pearson correlation coefficient, Yetman proposes using the absolute value of the difference between the quantities $g_i(t)$ and $g_j(t)$ (seen in the (2.4)) multiplied by -1, namely the same indicator proposed by Wälti multiplied by -1. As explained by Yetman, his alternative measure is intuitively appealing. For example, the three cases listed above, from point 1 to point 3, that generate $\rho_{ij}(t) = 0$ would be treated differently with the alternative measure. Case 3, where both economy's growth rates are equal to the respective average levels, would be seen as consistent with high synchronization rather than decoupling, in fact in this case the difference between $g_i(t)$ and $g_j(t)$is zero. On the other cases, 1 and 2, the alternative measure proposed by Yetman would evidence the distance between the growth rate and the average growth rate across the two countries.

The following Table 2.1 reproduces the results of Yetman (2011a). On a sample of 12 Asian countries and GDP data from 1971 to 2008, the author computes the Pearson correlation coefficients between the GDP growth rates of each of the 12 Asian countries and the US (columns *a* and *b*); he also computes the comovement between GDP growth rates using the alternative indicator he proposed (columns *c* and *d*).

As seen in Table 2.1, while the correlation coefficients (columns *a* and *b*) decline from the oldest sub-sample (1971-1989) to the late sub-sample (1990-2008) for many countries supporting the idea of Asian decoupling from the US, applying the alternative measure of economic comovement the results are mainly inconsistent with the decoupling idea.

Table 2.1 GDP growth rate correlations: Asia-Pacific with United States

	Usual Measure		Alternative Measure	
Countries	1971-1989	1990-2008	1971-1989	1990-2008
	a	*b*	*c*	*d*
Australia	0.47	0.73	-0.88	-0.41
China	0.49	0.12	-0.76	-0.77
Hong Kong	0.5	0.04	-0.95	-0.75
Indonesia	0.29	-0.34	-1.04	-1.54
India	-0.11	0.25	-1.32	-0.68
Japan	0.63	-0.14	-0.81	-0.81
Korea	0.49	-0.11	-0.86	-0.93
Malaysia	0.28	-0.06	-1.1	-0.93
New Zeland	0.34	0.33	-0.98	-0.59
Philippines	-0.15	0.12	-1.12	-0.63
Singapore	0.22	0.34	-1.11	-0.87
Thailand	0.39	-0.30	-0.99	-1.31

Source: Yetman J. (2011a).

5.3 Third critique: distortion due to heteroskedasticity

The third critique, namely that the correlation coefficient may be biased owing to the heteroskedasticity of the time series, is claimed by Forbes and Rigobon (2002).

The correlation of output growth rates between countries i and j mixes[27] two different components (see the following equation (2.6)). One is the structural link between the two economies, namely the sensitivity of the output growth rate of country j to the output growth rate of country i (β_{ij} in equation (2.6)); and the other one is the ratio of the output volatilities (σ_i/σ_j):

$$\rho_{ij} = \beta_{ij}\left(\frac{\sigma_i}{\sigma_j}\right) \qquad (2.6)$$

As can be seen from (2.6), even if the beta coefficient remains the same, the correlation increases when the volatility of the output growth rate of country i increases relative to the volatility of the output growth rate of country j; for example owing to the changes over time in the nature of the local shocks in country i which could modify the volatility of GDP growth rate of country i.

[27] See also Yeyati and Williams (2012).

This observation is particularly important because some previous studies showed that the ratio between the volatilities of different time series can change over time. For example, Kose et al. (2003c) measured the volatility of GDP growth rates of different countries. For the two groups of countries (industrial economies and developing economies) they computed the median volatilities. As can be deduced from their results, for both groups of industrial economies and developing economies the median volatility decreased from the 1960-1972 sub-sample to the 1986-2002 sub-sample and the ratio of the two median volatilities decreased, although slightly, from 0.6 to 0.5. So, when the decoupling phenomenon is studied by observing changes in the patterns of correlations, it is very important to remember that part of the explanation for changes in the correlation patterns can be due to changes in volatility (perhaps due to changes in the nature of country-specific and global shocks) in addition to changes in the structural linkages between the two countries (β_{ij}) which indeed is what really matter in studying the decoupling phenomenon.

Forbes and Rigobon (2002) proposed applying a correction to the correlation coefficients to take into account any changes in volatility from one period to another. Suppose we are interested in comparing the synchronicity of output growth rates between country i and j across two sub-samples, and suppose that the correlation coefficients obtained for the two sub-samples are respectively $\rho_{ij}^{(1)}$ for subsample 1 and $\rho_{ij}^{(2)}$ for subsample 2. Following Forbes and Rigobon, Yetman (2011a) shows it is incorrect to compare $\rho_{ij}^{(1)}$ and $\rho_{ij}^{(2)}$, instead one of them should be adjusted for the change in volatility between the two time periods, i.e. it is more correct to compare $\rho_{ij}^{(1)}$ and $\rho_{ij}^{(2*)}$ where

$$\rho_{ij}^{(2*)} = \frac{\rho_{ij}^{(2)}}{\sqrt{1 + \delta\left[1 - \left(\rho_{ij}^{(2)}\right)^2\right]}} \tag{2.7}$$

and

$$\delta = \frac{\sigma_{j2}}{\sigma_{j1}} - 1 \tag{2.8}$$

is the relative variation in the volatility of the output growth rate of country j between the first and the second sub-sample periods.

Using the method proposed by Forbes and Rigobon, Yetman (2011a) finds that the correction[28] had quantitatively important effects on the correlation coefficients, nevertheless he reached the same conclusions obtained from the unadjusted usual measure of the correlation coefficients (those showed in Table 2.1, columns *a* and *b*), namely declining correlation from the oldest sub-sample to the late sub-sample supporting the idea of Asian decoupling from the US.

In addition to the Forbes and Rigobon correction, a further way to overcome the heteroskedasticity-related distortion in evaluating the decoupling phenomenon is to estimate the parameter beta, namely estimating the structural link between countries (coefficient β in equation (2.6)). For example, this is what Yeyati and Williams (2012) did. They investigated decoupling by estimating the structural link between the output growth rates of EEs and AEs (more precisely 21 emerging countries and the members of the G-7 group). They regressed the GDP growth rates of EEs on the G-7 GDP growth rate in two panel regressions, one on the sub-samples 1993-200 and the other one on 2001-2010 period. They found decreasing betas, so they concluded in favour of real decoupling of EEs because, basically, they found a lower sensitivity of EE output growth rate to AE output growth rate in the last decade than in the previous decade. This approach to studying the decoupling phenomenon, which contains important contributions to the economic literature on the decoupling issue, will be described in more detail in section 7 of this chapter.

6. Breakdown of advanced and emerging countries' economic fluctuations

Some authors study changes in the nature of the economic cycle over time by employing the dynamic latent factor model to estimate global and country-specific components in the macroeconomic output. Their objective is to answer the following question: has the global factor become more important in explaining economic cycles in both advanced and emerging countries? If so, it means that the connection between AEs and EEs has increased over time, casting doubts on the decoupling hypothesis. As already mentioned (subsection 2.1), the contribution of the global factor is a measure of the extent of comovement across national business cycles, hence the above question may be

[28] As explained by Yetman, he used the Forbes and Rigobon correction knowing that it is strictly accurate when there are no omitted variables or endogeneity between markets, nevertheless it may provide an indication as to how sensitive the results are to changes in volatility.

rephrased as follows: have national economic cycles become globally more synchronized? This is basically the same question posed by the authors cited in section 5 above.

Kose et al. (2012), on the basis of the work of Kose et al. (2003, 2008), use a dynamic latent factor model[29] to break down the growth rates of national output, consumption and investment of 106 countries (23 advanced economies, 24 emerging economies and 59 developing economies) into the following factors: 1) a global factor, which captures fluctuations common across all variables and countries; 2) three factors specific to each group of countries (advanced economy factor, emerging economy factor and developing economy factor) which catch fluctuations common to all variables of the countries in the same group; 3) country factors common across variables in a given country; 4) idiosyncratic factors specific to each time series.

Their sample period ranges from 1960 to 2008 and, to study how economic cycles have evolved over time, the authors divide the sample into two separate periods. The first is the pre-globalization period (1960-1984) which was characterized by a set of common shocks associated with strong oil price fluctuations in the 1970s and synchronized contractionary monetary policies in some of the major industrial economies. The second is the globalization period (1985-2008) characterized by increasing global trade and financial flows.

Their major result is that there has been a decline over time in the importance of the global factor in accounting for national economic cycle fluctuations. In parallel, during the globalization period, the group factors have become more important than the global factor in driving national economic cycles in both the advanced economies group and the emerging economies group. So the authors conclude that there is evidence of economic cycle convergence within each of the two groups but divergence (decoupling) between them.

This conclusion is in line with the results presented in Mumtaz et al. (2011) on a dataset of 30 countries, 5 regions (North America, South Africa, Europe, Asia and Oceania), and annual data for GDP growth and inflation from 1860 to 2007. The authors apply the same econometric approach performed by Kose et al. and find that similarities in the growth rates of output increase within regions, while they decrease between regions.

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[29] The authors use a multifactor extension of the single dynamic factor model in Otrok and Whiteman (1998).

As Kose et al. (2012), Dong and Wei (2012) break down the economic cycle fluctuations into global, regional and country specific components. They use quarterly data for 16 countries (9 emerging Asian economies and the G-7 countries) from 1981:Q1 to 2008:Q4 of GDP growth rate and inflation. They find that, while the output fluctuations in emerging Asia have remained less linked with the global common factor than industrial countries, the Asian regional factor has become increasingly important in driving output fluctuations in emerging Asia. Also this results give support to the idea of decoupling although Dong and Wei's paper did not consider explicitly the distinction between AEs and EEs but instead divided the countries by geographical groups[30].

The papers mentioned above, based on the same econometric tools, reach the same conclusions in favour of the decoupling. Unfortunately, as with the correlation analysis, their approach does not allow disentangling the two forces which affect the path of the synchronicity, namely the effects due to changes in structural linkages and the effects due to changes in the nature of shocks. This point is well highlighted in the paper of Kose et al. (2012). The authors, in explaining their results, say that during the pre-globalization period there were two large common disturbances (the oil shocks) and certain correlated shocks in the major advanced economies (the austerity policies in the early 1980s), while during the globalization period common global disturbances have become less important. The authors highlighted that these phenomena may have led to a decline in the importance of the global factor in explaining national economic cycles during the globalization period. Hence, the finding of Kose et al. is not only the result of eventual changes in the structural linkages between AEs and EEs but it is also the result of the changing nature of shocks.

Canova and Ciccarelli (2012) investigated the economic fluctuations in the Mediterranean basin and explored similarities and convergence, breaking down national economic cycles into indicators representing regional components and country-specific components. They did not use the factor model, but instead used a panel VAR model with time varying parameters of the type developed in Canova and Ciccarelli (2009) and Canova et al. (2007). They used a dataset covering 16 countries (5 Western countries, 4 Eastern countries and 7 countries from the Middle East and North Africa) and GDP, consumption and investment growth rates from 1980 to 2010. One of their main results is that the time variations in the regional and country specific indicators are not in line with either convergence or decoupling because both phenomena are present but temporary. By

[30] In this case grouping countries by geographical regions is basically similar to grouping them by EEs group and AEs group.

comparing Pairwise rolling (10 years) correlations between the regional indicators, they found different periods of convergence (increasing correlation) and decoupling (decreasing correlation) across different regions.

7. Regression analysis and VAR estimations of spillover from AEs to EEs

Some authors study how economic sensitivity of some emerging countries to US country has changed over time. They use regression analysis to estimate the parameters representing the structural linkages between countries, or use impulse response functions with vector autoregression (VAR) model to evaluate for example how the spillover of shocks from US to some EEs has changed over time. These econometric tools, adding proper control variables as will be shown in this section, allow us to focus on the economic sensitivity of EEs controlling for the changing nature of shocks and the other sources of coefficient distortion.

With this approach, the question at which to answer is: has the sensitivity of emerging economies' output growth to the advanced economies' output growth decreased (decoupling) or increased over time?

Akin and Kose (2008) used a dataset of 106 countries (23 advanced economies, 23 emerging markets and 60 emerging and developing economies) covering 1960-2005. The authors estimated panel regressions relating GDP growth rate of the emerging economies vs. the GDP growth rate of advanced economies. The regression coefficients provided a measure of the magnitude of sensitivity of EEs to AEs. To control for different sources of GDP growth, the set of explanatory variables was extended to include several other output growth determinant such as the investment to GDP ratio, population growth, the government spending to GDP ratio and inflation. They found that the regression coefficient associated with the GDP growth rate of advanced economies is greater in the pre-globalization period than in the globalization period. From their estimated parameters, a 1 percentage point increase in the advanced economies GDP growth corresponds to 0.76 percentage points increase in the average GDP growth of emerging economies during the pre-globalization period, and this coefficient is about 0.4 percentage points higher than in the globalization period. This means that spillovers from advanced economies to the growth rate of emerging economies have declined in the globalization period compared to the earlier period.

Based on panel regression analysis, Alder and Tovar (2012) assessed for some emerging countries how the sensitivity of their output to an external financial shock varies across regions and time. Their analysis was based on quarterly data for a sample of 40 emerging economies and 9 advanced economies from 1990 to 2010. They used the S&P Chicago Board Options Exchange Market Volatility Index as the financial market stress indicator. Their main result is that, while still significantly vulnerable, both emerging Latin America and emerging Asia are less sensitive in recent years to external financial shocks than in the past. On the other hand, emerging European economies are now more sensitive.

While the results in Akin and Kose (2008) and Alder and Tovar (2012) are basically in favour of the decoupling hypothesis, Helbling et al. (2007) reached the opposite conclusion. On a dataset covering 130 countries and annual data over 1970-2005, Helbling et al. estimated panel regressions relating per capita growth of output in EEs to US growth, Euro Area growth, Japanese growth, and several control variables: terms-of-trade changes, a short-term interest rate, population growth, controls for the Latin American debt and Tequila crises, for the Asian financial crises of 1997–98, and for the Argentine crisis of 2001–02. The regression analysis suggested that the magnitude of the spillovers may have increased over time.

The evolution over time of the magnitude of spillovers was also described in Guimarães-Filho et al. (2008) which estimated the US spillovers to Asian emerging economies by both the estimated coefficients of the panel regression and the impulse response function performed using vector autoregressions (VARs). Like Helbling et al. (2007), Guimarães-Filho et al. (2008) did not find evidence in favour of decoupling. From the coefficients of the panel regression, Guimarães-Filho et al. concluded that spillovers from the US seem to have grown in recent years, in particular for China and India, because the estimated coefficients of the panel regression have increased between 1991-2001 and 2001-2007. This result was broadly consistent with that obtained with the impulse response functions performed using the VAR model. In fact, the impulse response functions showed that the impact of US shocks was lower for the 1980-95 sub-sample than the 1996-2007 sub-sample.

Dèes and Vansteenkiste (2007), following Stock and Watson (2003), estimated a Factor-Structural VAR model to explain GDP growth rate with the lagged growth rates, the common international shocks and the country-specific shocks. They used a dataset covering 23 countries (advanced economies, emerging Asia and emerging Latin America) on quarterly data from 1979 (2th quarter) to 2003 (4th quorter) and considered two sub-periods: 1979-1992 and 1992-2003. From their results evidence emerges in favour of the decoupling phenomenon. In particular, the spillover effects decreased from the sub-periods 1979-1992 to 1992-2003. Moreover it seems that emerging Asia tends to be mostly affected by regional shocks, while common shocks remain limited. For emerging Latin America it seems that the regional factor is the most important component in explaining the GDP growth rate, and its importance increases from the first sub-period to the second.

Dèes and Vansteenkiste (2007) work is particularly interesting because on the one hand, like for example Kose et al. (2012), it allows evaluation of the different components of the economic cycles, and on the other hand it also allows disentangling of the effects of structural interdependence (sensitivity) from the effects due to the different nature of shocks (common or country specific shocks), in fact the equation they estimated is:

$$Y_t = A(L)Y_{t-1} + v_t \tag{2.9}$$

Y_t is the vector of GDP growth rates, $A(L)$ is the coefficients matrix providing information about the sensitivity of EE GDP growth to AE GDP growth, while the error term v_t is broken down as follows

$$v_t = \Gamma f_t + \varepsilon_t \tag{2.10}$$

where f_t are the common international factors, Γ is the matrix of factor loadings, and ε_t are the country-specific shocks[31].

I believe that the approach described in this paragraph is particularly suited to the study of decoupling because it allows us to focus on the economic sensitivity of EEs while controlling for the changing nature of shocks. However it is important to make a series of observations on papers quoted in this paragraph. First, some of the papers quoted measure the sensitivity of several emerging countries to the U.S. economy. It is widely believed that the U.S. may be the leading economy in the world, but one should also consider other advanced countries for a more appropriate assessment of the phenomenon under discussion.

Second, some papers, even if they considered other EAs in addition to the U.S., used a set of countries rather smaller than those that were the ambitions of the research pursued. Using a small set of countries is not only very inappropriate with respect to the statistical significance of the observed sample, but also affects the realism of the model

[31] See Dèes and Vansteenkiste (2007) for more details.

used because it does not allow us to take into account the many economic interrelations between many countries observed in the real world. Considering the multiplicity of economic relations between many countries is crucial in the study of decoupling because one of the reasons adopted by supporters of decoupling in justifying the phenomenon is that the progressive increase of real and financial linkages among EEs may have favoured the strengthening of economic linkages within EEs while at the same time possibly favouring their moving away from AEs.

Finally, in all the papers cited decoupling is investigated by looking for a structural break in the estimated coefficients located roughly around the end of the eighties. This approach is appropriate and effective if the interrelationship between the countries is assumed to evolve in a discrete fashion over time. The introduction of structural breaks is less effective if the relationship between the countries follows a gradual progression over time, as it could be decoupling; thus, in this case it should be more appropriate to investigate the decoupling phenomenon by assuming that the coefficients can gradually change over time.

8. Analysis of shock spilliovers from AEs to EEs using micro-funded economic models

Another way forward in investigating the decoupling phenomenon is to follow a more structural approach by designing micro-funded economic models and examining the transmission of shocks from AEs to EEs through trade and financial linkages. The characteristic of this approach, which differentiates it from the approach presented in section 7 above, is that the theoretical base of the models is micro-funded and particularly rich.

Starting from the "real business cycle" (RBC) approach to economic dynamics, which originated in the pioneering work of Finn Kydland and Edward Prescott (1982), most models that emerged have essentially been built on rational expectation with the explicit incorporation of microeconomic behaviour of forward-looking economic agents. Mendoza (1991) developed an extension of the real business cycle framework to the case of a small open economy (SOE), providing a, let us say, “standard small open economy RBC model”.

Since then, a growing economic literature on emerging economies has extended the Mendoza (1991) model to take into account the empirical features of emerging market economies. This led to several evolutions of the "standard small open economy RBC model" in the form of both additional different shocks and nominal frictions, the latter considering the (new) Keynesian flavour in the RBC approach. Given this literature extension and its various aspects, it is useful to first focus on its main features, without entering into too much technical detail as it would be beyond the intentions of this survey, and then emphasize the contributions of the relative literature that directly investigated the decoupling phenomenon.

8.1 Micro-funded economic models: a brief excursus

The standard small-open-economy RBC model in Mendoza (1991) features a representative infinitely-lived household, a representative firm operating a neoclassical production technology subject to random productivity disturbance, and an international credit market of one-period bonds. In this model the credit market is perfect in the sense that the small open economy can borrow or lend any amount of financial assets consistent with the household's "no-Ponzi game" [32] condition at the "appropriate" market-determined real interest rate.

In this model, time is discrete and indexed by t=1,2,3…. There is only one type good in each period, which can be produced with a technology given by

$$Y_t = A_t F(K_t, \Gamma_t L_t) \quad (2.11)$$

Where Y_t denotes output, K_t capital available in period t, L_t labour input, and $F(\cdot)$ is a neoclassical production function and A_t is the total factor productivity

$$A_t = e^{z_t} \quad (2.12)$$

where z_t is a shock to total factor productivity, assumed to follow the process:

$$z_{t+1} = \rho_z z_t + \varepsilon_{z,t+1} \quad (2.13)$$

where $|\rho_z| < 1$ and $\varepsilon_{z,t}$ is an i.i.d. shock with mean zero and variance σ_z^2 . In this model the shock $\varepsilon_{z,t}$ is the only source of uncertainty, and the total factor productivity is a stationary process.

Γ_t is a term allowing for labour-augmenting productivity growth. In this basic standard model, Γ_t is assumed to follow a deterministic path:

$$\Gamma_{t+1} = e^{\mu}\Gamma_t \quad (2.14)$$

[32] The No-Ponzi game condition states that the present discounted value of wealth at infinity must be non-negative (Blanchard and Fisher, 1989, p. 49).

where μ is the constant growth of labour augmenting productivity.

Capital accumulation is given by the equation:

$$K_{t+1} = (1-\delta)K_t + I_t - \Phi(K_{t+1}, K_t) \tag{2.15}$$

where I_t denotes investment, δ the rate of depreciation of capital, and $\Phi(K_{t+1}, K_t)$ is the adjusting capital cost function. Adjusting capital cost functions are commonly used in the business cycle literature of small open economies in order to avoid excessive investment volatility. As explained in Mendoza, investment reacts very differently to productivity shocks in open-economy models than in closed-economy models. Access to foreign markets permits individuals to separate savings and investment by allowing them to finance any gap between the two from external resources. Mendoza (1991) shows that a small open economy model - in which capital can be freely accumulated without adjusting cost - exaggerates the variability of investment. This “anomaly” can be avoided by introducing moderate capital-adjustment costs, thus adopting the view that financial capital is more mobile than physical capital, a view previously explored by Dooley et al. (1987).

The economy is inhabited by a representative household with the following utility function:

$$U_t = U(C_t, 1-L_t) \tag{2.16}$$

Where C_t denotes consumption at time t, the total amount of time available for work or leisure is normalized at unity, and $U(\cdot)$ is a neoclassical utility function.

The representative agent has access to a world market of the only one type bund “B”. Her budget constraint is therefore:

$$C_t + I_t + B_t = w_t L_t + s_t K_t + \left(1 + r_{t-1}^f\right) B_{t-1} \tag{2.17}$$

B_t is the one-period real asset that household holds at time t, namely $B_t > 0$ (credit) if the household is a lender and $B_t < 0$ (debt) if the household is a borrower. The variable w_t denotes the real wage, s_t the real rental of capital, and r_t^f the international (foreign) real interest rate.

In Mendoza (1991), it is assumed that the real international interest rate is sensitive to the level of the country’s international financial position (lending or borrowing position) in the sense that the interest rate a country’s citizen pays on international borrowing is an increasing function of the country’s international debt, and the interest rate that citizens receive for international savings declines as a function of total savings. This assumption does not derive from a solution to the optimal borrower/lender problem, but it is coherent with observed practice in the current credit market. Moreover the assumption has a key role in open economy models for two reasons. On the one hand it reflects the concept of country risk, and on the other hand, as showed in Schmitt-Grohé and Uribe (2003), it "closes the model", that is it allows to find a single stationary state equilibrium. Note that in this basic standard small open economy the financial market is perfect, one in which the small open economy can borrow or lend any amount that is consistent with the household's no-Ponzi-game condition at the "appropriate" market-determined real interest rate.

In more formal terms, it is assumed that residents of this hypothetical small open economy face an international interest rate given by:

$$r_t^f = r^* + v(B_t) \tag{2.18}$$

where r^* is the world real interest rate assumed to be constant. $v(B_t)$ can be interpreted as a spread on r^*. $v(B_t)$ must be a decreasing function[33]. From the (2.15) and (2.17) and (2.18) we get the following equation:

$$C_t + K_{t+1} + B_t = w_t L_t + s_t K_t + (1-\delta)K_t - \Phi(K_{t+1}, K_t) \\ + \big(1 + r^* + v(B_{t-1})\big)B_{t-1} \tag{2.19}$$

The household chooses the sequence of values for $\{C_t, L_t, K_{t+1}, B_t\}_{t=0}^{\infty}$ to maximize the expected discounted utility, subject to constraint (2.19) and "no Ponzi game" condition.

The conditions for the solution of the utility maximization problem give the equilibrium conditions to which we have to add the factor payments conditions in order to arrive at the general equilibrium conditions. Given the production function (2.11) and the assumption that factor markets are competitive, the rental rate paid to the owners of capital s_t and real wage w_t, are given by marginal productivities

$$s_t = A_t F_k(K_t, \Gamma_t L_t) \tag{2.20}$$

$$w_t = A_t F_L(K_t, \Gamma_t L_t) \tag{2.21}$$

Where $F_K(\cdot)$ and $F_L(\cdot)$ are the partial derivatives of $F(\cdot)$ w.r.t. K and L respectively. Note that, as shown for example in Mendoza (1991), under the assumption of a production function homogeneous of degree one w.r.t. K_t and L_t, from (2.17), (2.20) and (2.21) the good market clearing condition holds, that is

$$Y_t = C_t + I_t + B_t - (1 - r_{t-1})B_{t-1} \tag{2.22}$$

Where the net trade balance at time t coincides with $[B_t - (1 + r_{t-1})B_{t-1}]$. So, given the initial conditions $\{K_0, B_0, r^*\}$, the competitive equilibrium of the economy is defined by the processes $\{C_t, L_t, K_{t+1}, B_{t+1}, w_t, s_t\}_{t=1}^{\infty}$ that solve the utility maximization

[33] For example, McCandless (2008) assumes $v(B_t) = -aB_t$, a is a positive constant. The minus sign says that as a country accumulate foreign debt, the international interest rate it pays will rise.

problem, satisfy the competitive market factor prices condition (2.20), (2.21) and the markets clearing conditions.

The Mendoza (1991) model was extended in different dimensions adding (a) shocks to productivity trend, (b) shocks to world interest rate, (c) shocks to terms of trade, and especially adding (d) nominal friction (sticky prices) and (e) credit market imperfection.

Aguiar and Gopinath (2007), introduces a stochastic productivity trend, in addition to the temporary productivity shocks already present in Mendoza's (1991) Small Open Economy Model. This seemingly small addition, Aguiar and Gopinath argue, goes a very long way towards addressing some of the known empirical figures of emerging market economies, including the strong counter-cyclical behaviour of trade surplus and the higher volatility of consumption relative to output.

Aguiar and Gopinath (2007), motivated by the frequent policy regime switches observed in emerging markets, have hypothesized that these economies are subject to substantial volatility in trend growth. Their model has the same framework as the Mendoza (1991) model with addition of the assumption of stochastic productivity growth Γ_t. So the assumption (2.14) is replaced by

$$\Gamma_{t+1} = e^{g_{t+1}}\Gamma_t \tag{2.23}$$

Where g_t follows the stochastic process

$$g_{t+1} = \left(1 - \rho_g\right)\mu + \rho_g g_t + \varepsilon_{g,t+1} \tag{2.24}$$

$\left|\rho_g\right| < 1$, $\varepsilon_t^g$is an i.i.d. process with mean zero and variance σ_g^2, and μ is the long-run mean value growth of labour-augmenting productivity.

g_t is the shock to productivity growth. We can refer to the realizations of g_t as the growth shocks since they constitute the stochastic productivity trend. A positive realization of $\varepsilon_{g,t}$ implies that the growth of productivity (labour productivity) is temporarily increased, however, such a shock is incorporated in Γ_t and hence results in a permanent productivity improvement.

That the addition of permanent productivity shocks has the potential to account for some stylized facts observed in some EEs is intuitively explained by a permanent income view of consumption. After a favourable realization of $\varepsilon_{g,t}$, productivity increases permanently. Accordingly, permanent income and therefore consumption can increase more than current income; this explains why consumption may be more volatile than income in emerging economies. The same reasoning implies that after a positive shock to the productivity growth rate the representative household may want to issue debt on the world market to finance consumption in excess of current income, leading to a countercyclical current account.

Neumeyer and Perri (2005) and Uribe and Yue (2006), motivated by the observation that the cost of foreign credit appears to be countercyclical in emerging economies data, propose to introduce foreign interest rate shocks to the Mendoza framework, coupled with the working capital assumption (namely the need for firms to finance a fraction of labour costs in advance) and a country risk determined endogenously as a function of shocks to productivity.

Qualitatively, the endogenous real interest rate spread and the "working capital" assumption should work as follows. With a spread process endogenously determined as a function of productivity, a favourable productivity shock increases output and reduces the interest rate applicable to representative household debts, thus boosting consumption and investment even beyond the boost to output, at the same time, with the working capital assumption, a drop in the world interest rate reduces the cost of labour, which stimulates output.

Let us modify the basic small open economy model to formally take into account the hypothesis proposed in Neumeyer and Perri (2005).

Firstly, the international interest rate equation (2.18) is modified to consider both the changing world interest rate and the specific country risk

$$r_t^f = r_t^* d_t \tag{2.25}$$

where d_t is the country-specific spread over r_t^* paid by borrowers in particular economy at time *t*. The assumption behind the equation (2.25) is that there are two forces at play in the interest rate dynamics faced by an emerging economy: international investors' attraction to risky assets captured by changes in r_t^*, and the specific country risk default captured by d_t.

The more important issue to resolve is what drives d_t. Neumeyer and Perri (2005) propose a minimal country risk model to conduct their quantitative analysis. Their idea is that fundamental shocks to a country's economy (in their model productivity shocks) drive the business cycle and country risk at the same time. In other words they assume that default probabilities and, hence, country risk are a function of productivity shocks. The functional relationship does not derive from a solution to the optimal borrower/lender problem, but is an assumption based on the idea that default probabilities are high when expectations of positive productivity shocks are low. Thus the country-risk component of r_t^f is a decreasing function of expected productivity, hence

$$d_t = \zeta(E_t[A_{t+1}]) \tag{2.26}$$

where $\zeta(\cdot)$ is a decreasing function. Note that in Neumeyer and Perri (2005) model the international real interest rate is not sensitive to the level of the country's international financial position (lending or borrowing position), so the model must be "closed"[34] in some other way. The authors propose closing their model by adding in the bond holding costs, $\kappa(B_t)$, where $\kappa(\cdot)$ is a convex function. At time t households spend the proceeds from bond holdings and their labour and capital income on consumption, investment, bond purchases and the cost of holding bonds. The household's budget constraint (2.17) is then given by

$$C_t + I_t + B_t + \kappa(B_t) = w_t L_t + s_t K_t + \left(1 + r_{t-1}^f\right) B_{t-1} \tag{2.27}$$

Under the assumption that the firm has to borrow $\theta w_t L_t$ units of goods during the period t (the working capital assumption), the real profit function of the firm is

$$\pi_t = Y_t - (w_t L_t + s_t K_t) - r_t^f \theta w_t L_t \tag{2.28}$$

where θ captures the importance of working capital. From the maximization of (2.28), under the assumption that factor markets are competitive, the condition (2.21) on equilibrium real wage becomes

$$w_t\left(1 + \theta r_t^f\right) = A_t F_L(K_t, \Gamma_t L_t) \tag{2.29}$$

Of course, if θ is set to zero, firms do not need working capital, the term capturing the cost of the working capital in the firm's profit function (2.28) disappears and the supply side of the model reduces exactly to the basic standard small open economy model presented at the beginning of this section.

More recently, Cicco, Pancrazi and Uribe (2010) presented an SOE RBC model which combines the features both of the Aguiar Gobinath (2007) and Neumeyer Perri (2005) models.

One dimension in which Emerging Economies differ from developed economies is that EEs rely heavily on a narrow range of primary commodities for their export earnings, and depend heavily on imported capital goods and intermediate input for domestic production. In the light of these structural features, it should not be difficult to see that fluctuations in world prices (fluctuations in the prices of primary, capital, and

[34] Remember that "model closure" means finding a single stationary state equilibrium and then being able to find a log-linear approximation of the dynamic model around the stationary state. See Schmitt-Grohé and Uribe (2003) for the ways of achieving "model closure".

intermediate goods, and in the world real interest rate) have an important impact on economic dynamics in small open emerging countries (M. Kose 2002). The role of world prices in inducing business cycles in Emerging Economies was explored in depth by Mendoza 1995, and then by M. Kose 2002. They borrow the RBC theory to compute the equilibrium processes of three sector models (non-tradable goods, exportable goods and importable goods) in a small open economy.

A large portion of recent empirical literature on emerging markets takes into account financial market imperfections. This literature proposes financial transmission mechanisms that can be roughly divided into two categories. As well-explained by Arellano and Mendoza (2002), in the first category we find studies that explore financial transmission mechanisms driven by a borrower's ability to pay. In these models, borrowers may be willing to repay their debts but their ability to do so is threatened by the realization of "bad" states of nature. Creditors aim to cover their exposure to this default risk by imposing lending conditions on borrowers (usually in the form of collateral or liquidity requirements) or by choosing to incur monitoring costs to assess a borrower's claim that he is unable to repay. The second category emphasizes a borrower's willingness to pay. In these models, borrowers optimally decide to renege on their debts when the expected lifetime payoff of defaulting, net of any default penalty, exceeds the expected lifetime payoff of repaying .

Quantitative application of "ability to pay" models in SOE setting is represented for example by Mendoza and Smith (2002), which considers a RBC model with two sectors (tradable and non-tradable) and with a borrowing constraint set in terms of a fraction of GDP. This model was extended by Mendoza (2008), adding an environment in which foreign creditors retain as collateral a fraction of the value of the economy's capital stock.

Collateral constraints are features of a variety of private credit contracts but when it comes to instruments like sovereign debt there is very limited scope for enforcing contracts featuring those constraints. In this context, a modelling approach based on "willingness-to-pay" considerations seems an appealing alternative. Arellano (2008) studies a small open economy that faces a credit-market participation constraint. In case of default, the country is punished by permanent exclusion from world financial markets, so default is not optimal whenever the expected useful life of staying in a credit relationship exceeds that of living permanently under financial autarky.

Nominal friction and credit market imperfections together with a monetary policy framework have been considered by authors such as Elekdag et al. (2005), Cespedes et al. (2004), Devereux et al. (2004), Elekdag and Tchakarov (2004), as well as Gertler et al. (2003), and more recently Gertler et al. (2007). These authors built upon the model with financial accelerator developed by Bernanke, Gertler, and Gilchrist (1999), extending the small open economy environment by adding sticky prices, an imperfect credit market and a monetary policy framework.

8.2 Micro-funded models' contribution to the debate on decoupling

It is clear that the degree of mathematical complexity has increased over time to improve the accuracy and realism of the micro-funded economic models. However, while the reduced form of models have empirically documented shock transmission from AEs to EEs, the small open economy models have found it difficult to account for foreign disturbances in EEs[35] despite their richness in terms of possible shocks and nominal frictions (see Hernàndez and Leblebicioğlu, 2011). This difficulty is probably the reason why, in spite of the extensive literature on small open economy models, only a small number of them have been directly used to investigate decoupling, as Hernàndez and Leblebicioğlu (2011) for instance.

Hernàndez and Leblebicioğlu (2011) develop a two-country real business cycle model in which one country represents the emerging market and the other represents the US market. The emerging country is characterized by a more risky and greater financial market imperfection with respect to that of the US.

In their model, financial linkages are established through borrowing and lending in the international markets and financial market frictions are adopted in their model as in Neumeyer and Perri (2005). The emerging country must pay an interest rate which reflects the risk level of the country, namely a spread on the US interest rate. As in Neumeyer and Perri (2005), changes in the country spread and the US interest rate affect goods production in the emerging country due to the working capital constraint.

The trade channel is defined as follows. Each country produces a non-traded good and is also completely specialized in producing a traded good.

Their model is estimated with seventeen quarterly time series for Mexico and the US from 1994 to 2007. From the results, they conclude that the spillover from the US to

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[35] In designing a small open economy model for Canada, Justiniano and Preston (2010) demonstrate that the inability of the model to generate spillover becomes more evident when the model is estimated instead of calibrated.

Mexico increased over time. While during the first part of the 1990s the Mexican economy's poor performance was driven prevalently by domestic shocks, in the second part of the 1990s the Mexican GDP growth benefited from US economic growth. Based on data of Mexican economy, their finding is against the decoupling idea.

9. Conclusion

Decoupling implies a break in a relationship that was previously more coupled and closely linked. There is no precise definition of decoupling and so the phenomenon has been interpreted in various ways.

Some authors focused on the historical path of synchronization between economic cycles of EEs and AEs by using the rolling windows correlation analyses, or by breaking down the economic cycles into their components, for example the common component and country-specific component. As explained in the paragraph 5 of this chapter, the historical path of synchronization between economic cycles may depend on two distinct forces. It may depend not only on the actual economic linkages between the countries, let us say the sensitivity of the economic cycle of a country to the economic cycle of the other country, but also from the way in which the nature of shocks changes over time. The correlation analysis and the breakdown of economic cycles do not allow disentangling of the effects of the two forces on the historical path of the synchronization. This observation is highly important because decoupling refers to how the economic linkage between advanced economies and emerging economies changes over time. It is a concept of structural significance regardless of the nature and type of shocks that can affect an economy from time to time in different historical periods. For this reason, a number of other authors (e.g. Akin and Kose, 2008) tried to study the phenomenon focusing on the sensitivity of some emerging country economic cycles to same advanced country economic cycles by controlling for the changing nature of shocks over time.

Given the different interpretations of the phenomenon, several authors have used different statistical/econometric techniques to analyze the data in their empiric studies; moreover, they have used different data and economic indicators.

As regards the statistical/econometric techniques adopted, these range from correlation analysis on a rolling time window to dynamic latent factor models to study the synchronicity of economic cycles in EEs and AEs, and from econometric estimations to simulations of micro-funded models to study the sensitivity of EEs' economic cycles to AEs' economic cycles.

With regard to the indicators, in some cases only GDP was considered, whilst in other cases a broader set of economic indicators, such as the industrial production index, consumption and investments for example, were used. In certain studies, e.g. Kose et al. (2008), a mere calculation of the short-term growth rate (year on year growth rate in the case of the paper cited) was used to extract the cyclical component from the time series; in others, such as Flood and Rose (2010), different methods were used to break down the time series into cycle and trend components, such as the Hodrick-Prescott or Baxter-King filters.

Basically, in agreement with Willett et al. (2011), the various interpretations of decoupling are useful and legitimate and, rather than wasting time discussing which is most suitable, it is important to clarify the type of concept to use as reference and document related conclusions in order to effectively contribute to the debate on this issue.

Therefore, if on the one hand the dissimilarity between interpretations of the phenomenon and investigative approaches can be confusing to those seeking to understand if and to what extent the economic linkage between EEs and AEs has changed, on the other hand those dissimilarity enhance the study of a phenomenon which is complex and wealth of aspects, namely a phenomenon which lends itself to observation from a variety of viewpoints.

Unfortunately, however, even in works based on the same concept of decoupling, conflicting conclusions are drawn. This uncertainty in results can be seen regardless of whether the statistical/econometric techniques used were sophisticated or simple.

Despite the fact that the decoupling hypothesis is long-debated, not only among academics, but also among policymakers and practitioners, it is still an open question both from a theoretical and empiric point of view.

The absence of a broadly accepted answer calls for further investigative efforts based on the most recent empiric study techniques and by steering studies both 1) towards large groups of countries and 2) towards specific countries.

Advancing research along the first path could prove useful in measuring how the degree of sensitivity of a group of countries to economic disturbances from other groups of countries evolves over time; and the use of a wider sample of countries, as in a Global VAR for example, could make simulations of international shock transmission more realistic; the next two chapters go along this direction.

Studies targeting specific countries, on the other hand, could be useful as case study in identifying existing relationships between the evolution over time of an emerging country's vulnerability to external shocks and the structural characteristics of its economy, e.g. its level of international openness, its geographic proximity to other countries, the availability and quality of its production factors or the implementation of country specific economic policies.

3. Is Decoupling in action?

1. Introduction

As explained in chapter 2, 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). It implies two main 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.

Among the numerous works that have investigated the two points mentioned above, see the survey in chapter 2, there are some particularly important to contextualize this chapter, that is Kose et al. (2012) and Wälti (2012) (which have focused the point 1), Guimarães-Filho et al. (2008), Dèes and Vansteenkiste (2007) (which have focused the point 2). For the convenience of the reader, let me recall briefly the contributions of their works.

Kose et al. (2012)[36], similar to Kose et al. (2003), perform their investigation on a dataset of 106 countries, employing a dynamic factor model[37] to decompose the national economic cycles of each country into different components[38]. 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 cycles[39] of 30 emerging and 26 advanced markets, concludes that there is no evidence in favour of the decoupling; rather, the comovement of the economic

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

[37] See Kose et al. (2003) for details on this approach.

[38] 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, and AEs, respectively; and country-specific factors, representing the specific economic dynamic of each national economic cycle.

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

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.

Guimarães-Filho et al. (2008) estimated the US spillovers to Asian emerging economies by the impulse response function performed with the vector autoregressions (VARs). The impulse response functions showed evidence against the decoupling because 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 rate with the lagged growth rates, the common international shocks and the 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.

Two crucial points for understanding the decoupling phenomenon have been no fully considered in Guimarães-Filho et al. (2008) or Dèes and Vansteenkiste (2007). The first point is that investigating the decoupling looking for a structural break in the estimated coefficients in a certain point of the time could not be a very good strategy when the relationship between the countries follows a gradual progression over a longer time, as it could be for the decoupling. In this last case, it should be more appropriate to investigate the decoupling phenomenon by assuming that the model's estimated coefficients can gradually change over time. The second point is the number of countries in the sample set. As already known, using a small set of countries affects the realism of the empirical model because it does not allow to take into account the many economic interrelations between countries (in particular between EEs) which instead are crucial in studying the decoupling because, for example, one of the reasons adopted by the supporters of decoupling in justify the phenomenon is that the progressive increase of real and financial linkages among EEs may have favored the strengthening of economic linkages within EEs while at the same time may have supported their moving away from AEs.

The purpose of the present chapter is to study the decoupling phenomenon by measuring how the resilience of EEs has changed over time. It extends the empirical research on the decoupling in different dimensions. First, unlike the prevalent literature, this chapter 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 divide the sample period in the "pre-decoupling" and the “post-decoupling " one, but rather the sensitivity of EEs is assessed in each year of the entire sample period. Second, this chapter, 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 advanced economy countries.

In this chapter I have also evaluated the economic correlation between the two groups of countries to get a richer set of empirical evidence.

Two recently developed econometric tools: the Euclidean distance proposed by Wälti (2012) and the time-varying Panel VAR model with factorization of the coefficients[40], as proposed by Canova and Ciccarelli (2009)[41], were used to study a sample of 112 countries (of which 23 advanced countries, 59 emerging countries and 30 developing countries) on annual data from 1970 to 2010.

The Euclidean distance between two standardized series conveys the same qualitative information as the correlation coefficient, moreover 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; hence the Euclidean distance may be used to better evaluate the changes in the correlation over time.

The model with the factorization of coefficients as 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 work. 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.

[40] 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).

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

Second, The model specification is well suited for investigating how the international transmission of shocks form 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 analysis to evaluate the response of EEs to adverse scenarios in AEs in a global framework. Finally, thanks to time varying coefficients it isn't necessary to implement a structural break in the model parameters. I believe that, as already said, 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.

The empirical investigation of the resilience of EEs was performed in two steps.

In the first step, 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 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, i.e. North and Central America, Latin America, Europe, Asia, Middle East and North Africa [MENA], Sub-Saharan Africa [SSA], Oceania) 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.

In the second step, the specification which got the greatest support by data 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 each year 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 highlighted 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. The analysis of the Euclidean distance fails to provide any clear and prevalent evidence in favour of the decoupling hypothesis. Nevertheless, in evaluating the results of this analysis it is important to consider that the degree of correlation between EEs and EAs, namely the value of the Euclidean indicator, 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 changes 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 the last twenty 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 ten 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 1990s.

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

2. Empirical analysis of the decoupling hypothesis

2.1 Countries and dataset

The data come from the Penn World Table 7.1[42] database that covers 112 countries (of which 23 advanced countries, 59 emerging countries and 30 developing countries) with annual data from 1970 to 2010. From the geographical point of view, in the country set there are 3 Central and North American countries, 29 Latin American countries; 17 Asian countries, 24 European countries, 11 Middle East and North African countries (MENA), 25 Africa Sub Saharan countries (ASS), and 3 Oceania countries;

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

they cover more than 90% of the world's GDP (at PPP) and more than 85% of the world's population[43] (see the appendix A for the list of all countries).

According to Pritchett (2000) and Abdul Abiad et al. (2012), 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. However, 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.

The countries used in this work are only those with a data quality grade[44] of "C" (or higher) in the Penn World Table 7.1.

To the end of using a broad selection of countries, in this chapter I focused on just one of the most important economic variables, that is, the annual rate of growth of real Gross Domestic Product (per capita, at purchasing power parity), and I used annual data.

Some authors, such as Kose et al. (2012), focus on the growth rate of the real Gross Domestic Product (not per capita) as a measure of the economic cycle. However, as

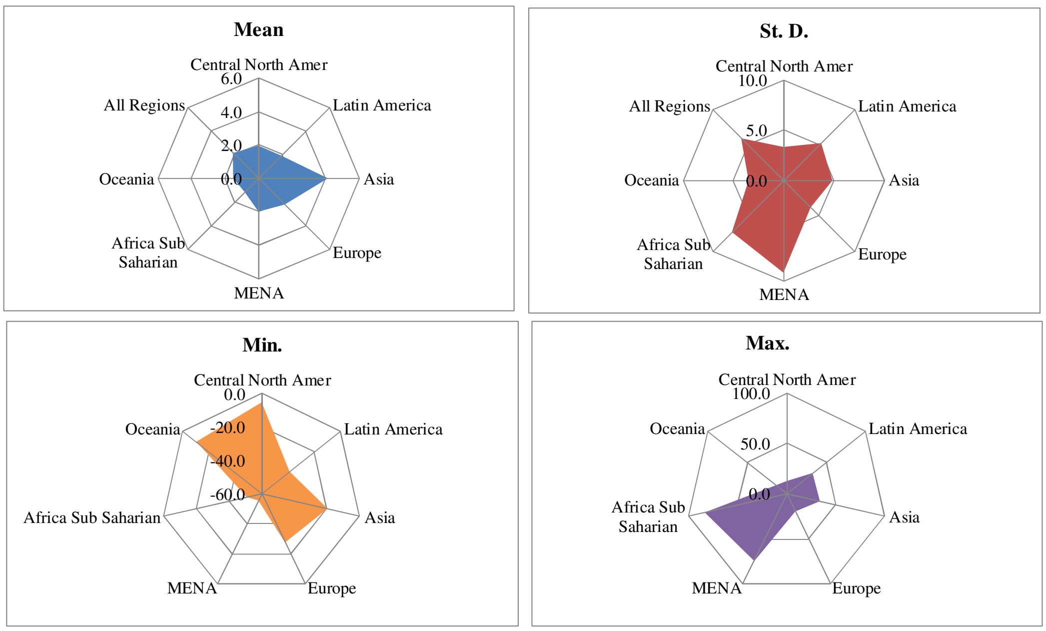


Fig. 3.1 Main stylized facts of GDP growth rate (%) along the regional dimension

[43] Own computation on data provided by the IMF, WEO Database, April 2013.
[44] The grade is a judgment on the quality of data expressed by the author of the dataset. The grade goes from D (low quality) to A (high quality); see the cited authors for more details.

was recently outlined by Reinhart and Rogoff (2012), the impact of population growth on real Gross Domestic Product growth rate is an important consideration when working with historical series. The real Gross Domestic Product growth rate can be misleading when the population growth rate changes significantly, as is the case in many EEs. Therefore, in this work, the real gross domestic product per head at purchasing power

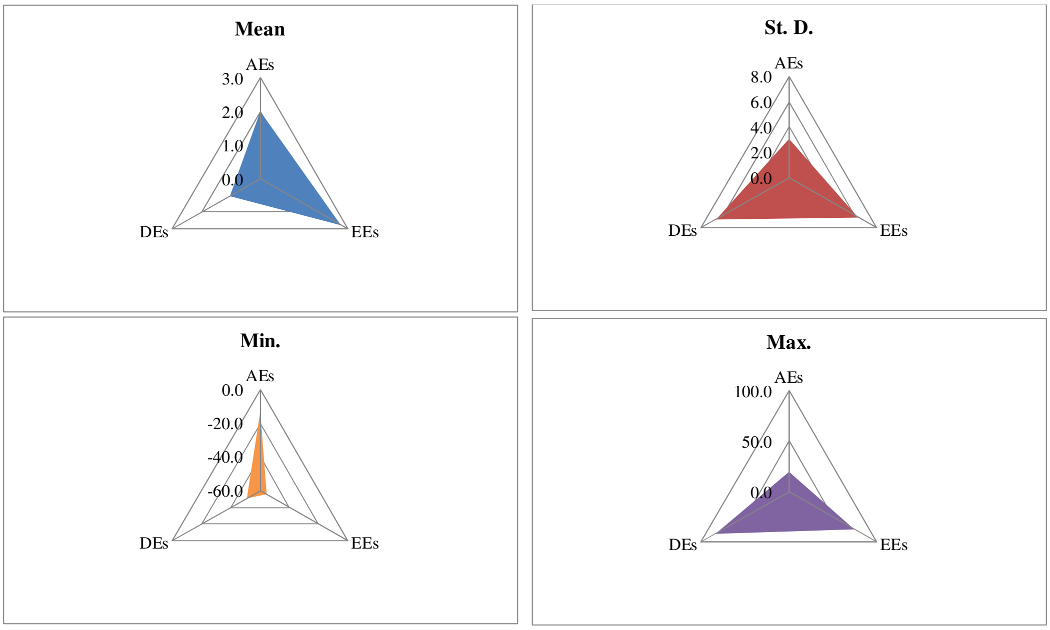


Fig. 3.2 Main stylized facts of GDP growth rate (%) along the economic type dimension

parity (from now on simply GDP) was used.

Given the time and the geographical dimensions, the dataset has high heterogeneity. In the entire dataset the average GDP growth rate (in per cent point) is 2.1 with a standard deviation at 5.9, the minimum at -55.5 and the maximum at 83.7. If we explore the main stylized facts along the regional dimension (Central North America, Latin America, Asia, Europe, MENA, ASS, Oceania), ignoring the economic type dimension (AEs, EEs and DEs), we find the Asian region to have the highest average GDP growth rate, about twice as much as the average of the entire dataset (see Figure 3.1); moreover, as highlighted in Figure 3.1, the ASS and the MENA regions have the highest standard deviations, and the highest contraction of the GDP growth rate is recorded within the MENA region, while the record high is recorded within the ASS area.

Exploring data along the economic type dimension (see Figure 3.2), it can be noted that the average GDP growth rate in EEs is the highest, and the greatest standard deviation is in the DEs group, where there is the lowest average economic growth too, while in the AEs group the standard deviation is the lowest.

From Table 3.1 it is possible to see the main stylized facts for sub-group of countries “crossing” the regional and the economic type dimensions[45]. It is interesting to note that, among the EEs, the Asian emerging countries have the highest average rate of GDP growth while in the MENA emerging countries there is the highest standard deviation. Among the AEs, the Asian advanced economy countries have the highest average growth rate while within the European advanced economy group there is the greatest standard deviation.

Table 3.1 Main stilized facts of the GDP growth rate (%) in sub-groups of countries

	Central North America				Latin America				Asia				Europe				MENA				Africa Sub Saharian				Oceania				All Regions			
	Mean	St. D.	Min.	Max.	Mean	St. D.	Min.	Max.	Mean	St. D.	Min.	Max.	Mean	St. D.	Min.	Max.	Mean	St. D.	Min.	Max.	Mean	St. D.	Min.	Max.	Mean	St. D.	Min.	Max.	Mean	St. D.	Min.	Max.
AEs	1.8	2.4	-5.5	6.6	n.a	n.a	n.a	n.a	2.3	3.0	-7.1	9.6	2.1	3.2	-13.0	19.5	n.a	n.a	n.a	n.a	n.a	n.a	n.a	n.a	1.5	2.4	-10.3	5.6	2.0	3.0	-13.0	19.5
EEs	n.a	n.a	n.a	n.a	2.1	5.2	-17.9	32.7	4.7	5.1	-19.7	33.8	2.7	5.2	-27.6	13.7	2.1	9.4	-55.5	74.5	3.0	7.6	-25.5	35.1	n.a	n.a	n.a	n.a	2.8	6.3	-55.5	74.5
DEs	2.2	4.7	-5.2	12.5	0.4	5.8	-38.7	29.3	2.5	3.7	-12.3	10.7	n.a	n.a	n.a	n.a	1.2	7.1	-14.7	22.1	0.8	7.2	-50.8	83.7	1.5	5.0	-8.6	13.5	1.0	6.7	-50.8	83.7
All Types	1.9	3.3	-5.5	12.5	1.9	5.3	-38.7	32.7	4.1	4.9	-19.7	33.8	2.2	3.8	-27.6	19.5	2.0	9.2	-55.5	74.5	1.2	7.3	-50.8	83.7	1.5	3.5	-10.3	13.5	2.1	5.9	-55.5	83.7

2.2 Synchronicity of national economic cycles

The aim of this sub-section is to investigate whether the comovement (synchronicity) of the economic cycles of EEs and AEs show a decreasing path in the last 40 years or not.

2.2.1 Method

Economic cycle synchronicity is usually measured as the correlation between economic variables 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 (2010), 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 for the estimation. For this reason, in this chapter, the economic cycle synchronicity was evaluated by using the measure proposed by Wälti (2012): namely, the Euclidean distance between two standardized variables.

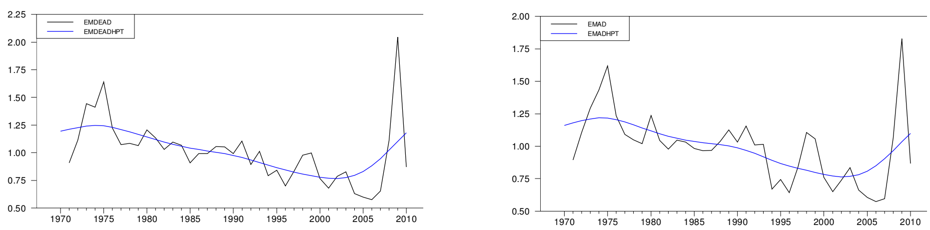
The Euclidean distance[46] is the absolute value of the numerical difference between two standardized time series[47] at each time t. When the difference is zero at time

[45] See appendix B for descriptive statistics of GDP data for each country.
[46] See the article of Wälti for details on the Euclidean method.

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, its advantage is that it can be computed for each year and also allows for the proper evaluation of the synchronicity of the time series at the end of the sample period. I computed the Euclidean distances 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 economies) with the group of all advanced economies. The measure of the economic cycle synchronization for each group was the average of the Euclidean distance of the group members[48].

2.2.2 Results

Figure 3.3 shows the degree of economic cycle synchronization, namely comovement, of the group of all EEs plus all DEs with the group of all AEs (panel 1) and the degree of economic cycle synchronization of EEs with AEs (panel 2), the blue lines indicate the Hodrick-Prescott filter. Since the second half of the 1970s, the comovement 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



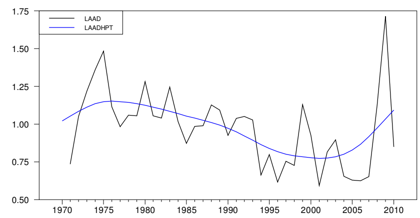
1 EEs plus DEs vs. AEs   2 EEs vs. AEs

Fig. 3.3 Euclidean distance: EEs plus DEs vs. AEs and EEs vs. AEs

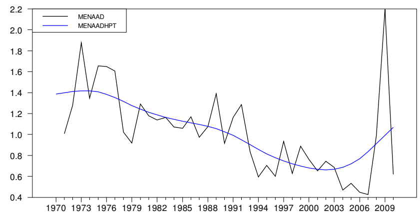
47 The GDP growth rate of each country was standardized by subtracting its mean and dividing by its standard deviation and then the synchronicity was evaluated through the Euclidean distance indicator.
48 The unweighted average was chosen because the data were "per head" and, thus, already weighted by the dimension of the country.

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 years[49].

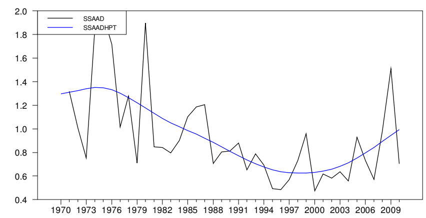
To check if the above results were general and reflected similar figures in subsamples of EEs grouped by geographical area, the synchronicity of economic cycles of five EE subgroups (Latin American, MENA, SSA, Asian, and European emerging economies) with all AEs was plotted in Figure 3.4. The pattern of the subgroups[50] was substantially consistent with the correlation shown in the Figure 3.3, 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 3.4, from panel 1 to 3), whereas the synchronicity showed a more gradual path for the emerging Asian countries (Figure 3.4, panel 4) and an almost-flat path for the European emerging countries (Figure 3.4, panel 5)[51].



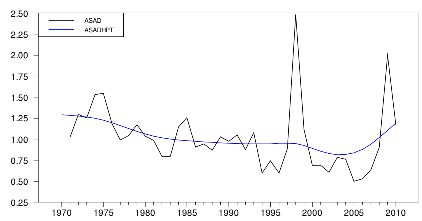
1.Latin America EEs vs. AEs



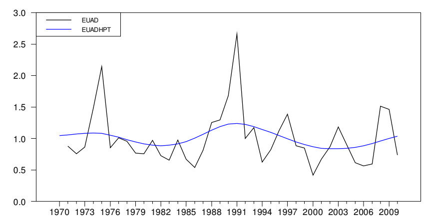
2. MENA EEs vs. AEs



3. SSA EEs vs. AEs



4. Asia EEs vs AEs



5. Europe EEs vs. AEs

Fig. 3.4 Euclidean distance: EEs regional groups vs. AEs

[49] 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 period, he was unable to observe the temporary jump of the indicator in 2009.

[50] The results of each single emerging economy are available on request to the author.

[51] The same conclusions were got when the deviation cycle, instead of the growth cycle, was used (namely the same definition of economic cycle used by Wälti (2012). See the appendix C for these results.

In general, the results suggest that insofar as the degree of correlation between EEs and AEs may be determined by the decoupling phenomenon, there isn't any clear and prevalent evidence of decoupling. Unfortunately 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 which have become more (or less) global than before[52]. 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 on the decoupling phenomenon, the information offered by the Euclidean distance indicator is not so accurate since the indicator does not allow 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, and so it is important to go more in deep in the empirical investigation through analysis enabling us to measure the influence of the AEs on the EEs and to measure how this influence has changed over the course of time. I have tried to do so by means of the simulation experiments presented in the following section.

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

In this Section a time-varying Panel VAR model with factorization of coefficients, of the type developed in Canova and Ciccarelli (2009) and Canova et al. (2007), was applied to decompose GDP 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.

2.3.1 Econometric model

The empirical model employed has the following form

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

[52] For more details on this point see the sub-section 5.3 in chapter 1.

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 column vector $G \times 1$, $y_{it} = (y_{it}^{1}, \dots, y_{it}^{G})'$; $Y_t = (y'_{1t}, \dots, y'_{Nt})'$ is a column vector with dimension $NG \times 1$; $d_{it,L}$ is the matrix of coefficients with dimension $G \times NG$ for $L = 1, \dots, p$; c_i is a vector $G \times 1$ of constant terms for the country i, and the vector of errors e_{it} has dimension $G \times 1$.

The system of equations can be written as follows:

$$Y_t = \sum_{L=1}^{p} D_{t,L} Y_{t-L} + C + E_t \quad E_t \sim N(0, \Omega) \tag{3.1}$$

where $D_{t,L}$ is an $NG \times NG$ matrix which contains the $d_{it,L}$ matrices as follows $D_{t,L} = \begin{bmatrix} d_{1t,L} \\ \cdot \\ \cdot \\ d_{Nt,L} \end{bmatrix}$; $C = (c'_1, \dots, c'_N)'$ is $NG \times 1$ vector; and E_t is a column vector $NG \times 1$ of random disturbances, namely $E_t = (e'_{1t}, \dots, e'_{Nt})'$, for which a normal distribution is assumed.

The system of equations (3.1) displays some peculiarities 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; 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 appreciable characteristic of the model have a cost. To illustrate this cost, the system of equations (3.1) can be rewritten as follows:

$$Y_t = W_t \delta_t + E_t \tag{3.2}$$

where $W_t = I_{NG} \otimes X'_t$; $X'_t = (Y'_{t-1}, Y'_{t-2}, \dots, Y'_{t-p}, 1)$, I_{NG} is the identity matrix $NG \times NG$ and the symbol $\otimes$ stands for the Kronegher product; δ_t is the column vector of parameters at time t, namely $\delta_t = (\delta'_{1t}, \dots, \delta'_{Nt})'$ and, for $i = 1, \dots, N$, δ_{it} is $G(GNp +$

1) $\times$ 1 vector containing stacked the G rows of the matrix $d_{it} = (d_{it,1}, \dots, d_{it,p}, c_i)$ whose dimension is $G \times (NGp + 1)$.

2.3.2 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 the column vector 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[53]. 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[54], 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 $(dim(\theta_t) \ll dim(\delta_t))$:

$$\delta_t = \Xi\theta_t + u_t \quad u_t \sim N(0, Z) \tag{3.3}$$

In eq. (3.3), u_t is the vector of residuals; Z is assumed to be $Z = \Sigma \otimes V$; and $\Sigma = \Omega$ as is standard in related literature[55] (see Kadiyala and Karlsson 1997). Given that the factors have similar units, a spherical assumption is adopted on V, namely $V = \sigma^2 I_K$ where I_K is the identity matrix $K \times K$ and σ^2 is a constant parameter. 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 $dim_f \times 1$, and so θ_t is a column vector whose dimension is $\sum_{f=1}^{F} dim_f \times 1$.

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

[53] These two options have been adopted in the literature (e.g., see Holts Eakin et al. (1988) and Binder et al. (2000)).
[54] See Canova and Ciccarelli (2009) for more details on the factorization of coefficients and its economic interpretation.
[55] This assumption allows considerable simplification in the calculus of the posterior density functions of parameters.

δ_t that are common across all countries; the vector θ_{2t}, whose dimension is $1 \times s$, captures movements in the coefficient vector δ_t that are common across the g geographical groups of countries; and the vector θ_{3t}, whose dimension is $1 \times N$, captures movements that are specific to the N countries. In this example, at time t it is needed to estimate $(1 + s + N)$ parameters while $dim(\delta_t) = NGK$, and so $(1 + s + N\,)$ must be lower than NGK to have useful factorization.

As explained by Canova and Ciccarelli, 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.

From an economic perspective, the factorization decomposes Y_t in different components that have an economic interpretation. To illustrate this point, eq. (3.3) can be substituted into eq. (3.2), and given the assumption on the variance/covariance matrix Z we have (see Canova 2007, Del Negro and Schorfheide 2011, or Canova and Ciccarelli 2013, among others):

$$Y_t = \mathcal{W}_t\theta_t + \, v_t \quad v_t{\sim}N(0, \sigma_t\Omega) \tag{3.4}$$

where $\sigma_t = (1 + \sigma X_t'X_t)$, the vector of residuals is $v_t = W_t u_t + E_t$, and the residuals in (3.2) and (3.3) are assumed independent. The regressors are $\mathcal{W}_t = W_t\Xi$, namely the averages of certain right-hand-side variables[56] of the original VAR specification (3.1). Economically, with eq. (3.4), the vector of dependent variables Y_t can be decomposed in, for example, common and country-specific cycle indices; in fact, when for example $\theta_t = (\theta'_{1t}, \theta'_{2t})'$ with θ_{1t} of dimension 1×1 and θ_{2t} 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. It must be noted that 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.

2.3.3 Transition equation

To estimate the model, the empirical specification must be completed with the transition equation[57] of θ_t, namely, the time-evolution of the vector of factors θ_t.

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[56] Given the equal weighting scheme used in averaging the variables of the original VAR, all data have been standardized.
[57] Known as the "evolution equation" in the jargon of the state space model.

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. Under the latter condition, it could be more appropriate to assume coefficients can gradually change over time.

In this paper, it was assumed that θ_t evolves over time by following a random walk[58]:

$$\theta_t = \theta_{t-1} + \eta_t, \quad \eta_t \sim N(0, B) \tag{3.5}$$

where the stochastic term η_t in (3.5) 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 the column vector θ_t, namely $R = \sum_{f=1}^{F} dim_f$.

To summarize, the empirical model has the following state space structure[59]:

$$\begin{cases} Y_t = W_t \Xi \theta_t + \upsilon_t & (3.6) \\ \theta_t = \theta_{t-1} + \eta_t & (3.7) \end{cases}$$

Where the residuals υ_t and η_t are assumed to be independent and have the conditional distributions as in (3.4) and (3.5), respectively.

To compute the posterior probability density functions (pdf) of the parameters of the empirical model it is needed to do assumption on the prior densities for Ω, σ^2, B and θ_0. 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 and the values of hyperparameters are shown in Appendix D, which shows also the conditional posterior distributions of the model parameters and provides details on the numerical approach used to sample them from the conditional posterior distributions.

[58] 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. (3.3) is thought to be in place for a finite period of time and not forever.

[59] The equation for the economic variables is also known as the "observation equation" in the jargon of the state space model.

The model shown in eq. (3.6)-(3.7) has been estimated by the Bayesian methods because the Bayesian approach allows the sample distribution of the parameters of interest to be obtained even when T and N are small.

2.3.4 Use of the model to investigate the decoupling hypothesis

The model has been estimated with the GDP growth rates coming from the dataset presented in the section 2.1 of this chapter, with annual frequency and one lag in the explanatory variables[60]. Before the estimation, the GDP growth rates have been standardized[61] to make coherent the equal weighting scheme in the system (3.6)-(3.7).

Through the counterfactual analysis experiments, the estimated Panel VAR model was used to investigate how the resilience of the EEs changed over time. Responses of the emerging countries economic cycles to simulated adverse scenarios affecting the advanced countries economic cycles were quantified through CA experiments in different years, and the results were compared to identify any tendencies in the changes.

The experiments performed in this work are the differences between two conditional expectations[62] (see Canova and Ciccarelli 2009 for more details on this method). In one case, the conditional expectation is the one the model, estimated using the data prior to time t when the supposed shock appears[63], would have obtained for the GDP of each country on the time horizon $t+\tau$ ($\tau = 1,2,3,\ldots$ for example) based on the hypothesis that the actual GDP growth rates of each advanced economy in the year t of the simulated shock were reduced by 1.0 point[64] (one-time shock). In the other case, the conditional expectation of GDP is the one the model would have obtained based on the actual GDP growth rate of each AE at time t. Given the way in which the experiment has been designed, the shock is given by the difference between the counterfactual and the

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[60] So the number of lags, indicated with p in the presentation of the model, is equal to 1.

[61] Each series has been standardized by subtracting its mean and dividing by its standard deviation; accordingly, each series has zero mean and unit variance.

[62] The conditional expectations are computed orthogonalizing the covariance matrix of the reduced form shocks, assuming that AEs block comes first; a natural choice given the patterns of trade, remittances and capital flows discussed in the second chapter.

[63] Part of the experiments presented in this section have been performed also using the model estimated on the entire data sample (1970-2010). See the appendix F for more details.

[64] Remind that before the estimation of the model the data have been standardized. This makes coherent the equal weighting scheme in the system (2.6)-(2.7) and also makes easier to interpret the comparison across time of the results of the simulations.

actual GDP growth rates of the AEs, namely a negative shock of 1.0 point[65]. Such an experiment pose the question: what would have happened to the GDP dynamics in EEs if the GDP dynamics in AEs had been 1.0 point lower than actually were

Let me precise that, since the identification scheme has little economic content, it is not possible to give responses any structural interpretation; for example I cannot say whether policy matters or not, and whether the shock I consider is a technological one, but this exercise is still useful for the purpose of this work as it allows us to observe how the resilience of the EEs changed over time.

Three different model specifications were implemented, and the model with the greatest support of the data[66] was used to perform the CA exercises. The specifications of three models differed from each other in their factorizations. The model specifications included the global factor (i.e., the factor that was common to all countries) and the country-specific factors in all three models, together with the group factors (i.e., the EEs, the DEs, and the AEs factors) in the second model or the regional factors (i.e., factors that were common among countries in the same geographical region: North and Central America, Latin America, Europe, Asia, Middle East and North Africa [MENA], Sub-Saharan Africa [SSA], Oceania) in the third model.

2.3.5 Results

The first step was to determine which of the three models was most supported by the data. According to the marginal likelihood calculations[67], 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

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[65] Let me note that, given that data have been standardized, in all cases I am simulating a 1.0 standard deviation shock. It is assumed that the shock does not alter the law of motion (3.7), so the estimated low of motion is used to compute $\theta_{t+\tau}$ over the horizon for which we are computing expectations. With my random walk assumption on equation (3.7), this is equivalent to freezing the coefficients at their end-of sample values (on this point see Canova and Ciccarelli, 2009).

[66] 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; mutatis mutandis for $\ell_{j^*}(\alpha_{j^*}\,;\,Y)$ and $P(\alpha_{j^*})$. For details, see Lancaster (2005), for example, among others.

[67] Marginal likelihoods are computed as harmonic mean (Newton and Raftery 1994).

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	-14080	-14093	-14060

Table 3.2 Estimated Log marginal likelihood of models.

compared). On the basis of Jeffreys Guidelines[68], 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 3.2 reports the marginal likelihood in logarithmic terms.

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

2.3.5.1 Global and regional cycles

Figure 3.5 displays the median (black line) and the posterior credible interval (16th and the 84th 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 some of 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 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 a rebound in 2010.

Consistent with other studies (see Backus and Crucini, 2000), fluctuations in oil prices seemed to be related to turning points of the global economic cycle, in fact 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 was associated with global recessions.

The Europe region indicator (panel 2) displayed five recessions from the early 1970s until 2010 which were located around the official CEPR dates for the whole Euro area[69]. The synchronicity of the cyclical fluctuations in the region showed changes over

[68] See Greenberg (2008), pp. 35.
[69] Recession dates: 1974Q3-1975Q1, 1981Q1-1982Q3, 1992Q1-1993Q3, 2008Q1-2009Q2.

time, in fact the dispersion was largest around the cyclical trough; namely, the posterior credible intervals were wider at those dates. Let us note that the most recent recession appeared to be deeper than the previous ones as 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 around the official NBER dates for the USA[70], 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. Let us note that 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 period.

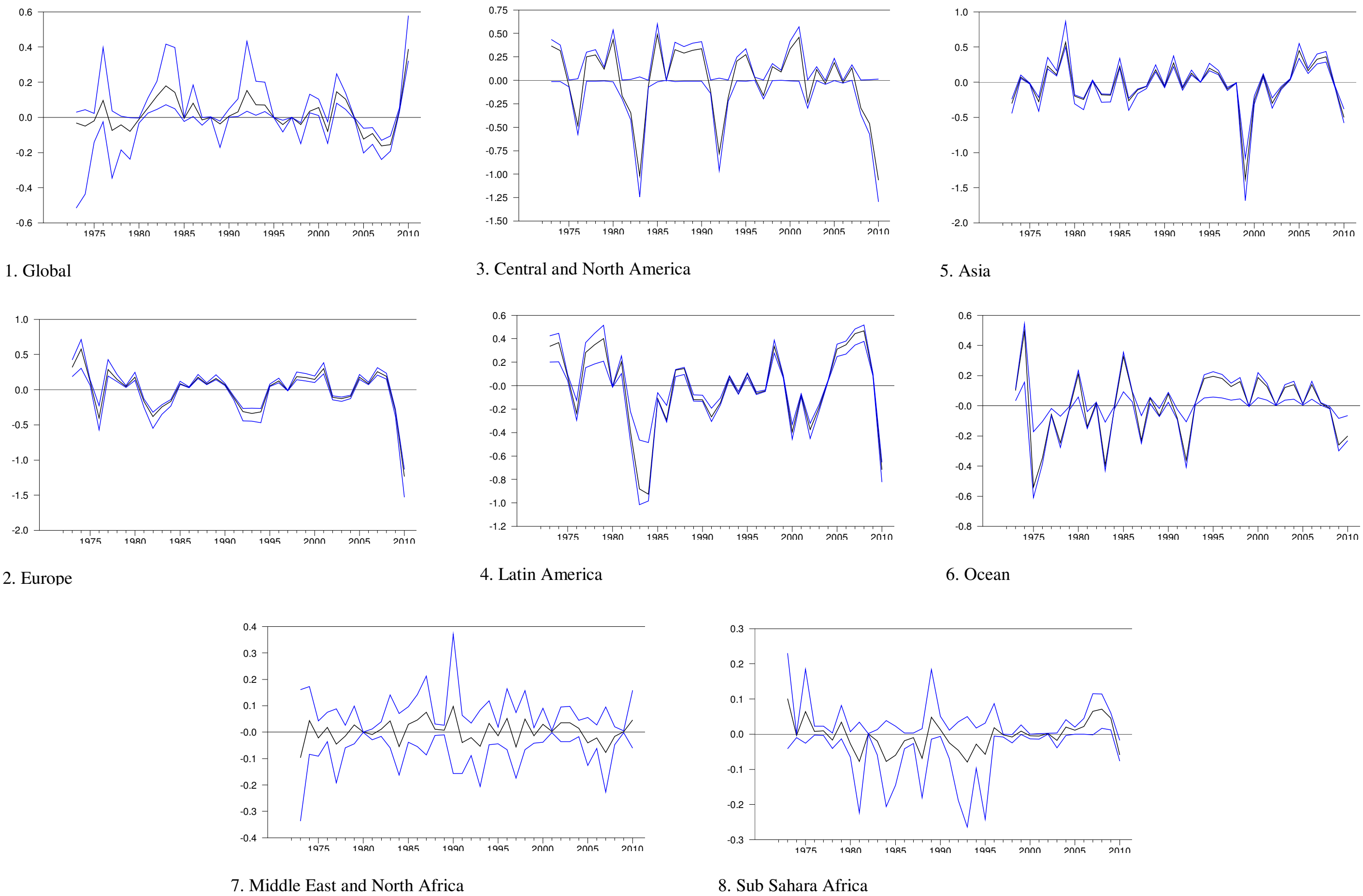


Fig. 3.5 Global and Regional Indicators

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

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, and the regional cycle also showed a phase of significantly long expansion from 2002 to 2007. The synchronicity of the cyclical fluctuations in this region showed changes over time. Since 1993, the dispersion of the indicator has been lower (lower posterior credible intervals) than that of previous periods.

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 economic recovery from 2002 to 2008 had just one previous similar period of strong economic expansion during the 1970s; instead 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 ones. The sample period can be divided in two subsamples, 1973-1992 and 1993-2010, with the economic cycle appeared to be more stable 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) displayed numerous ups and 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 slightly tighter after 1998.

The appendix E presents the historical decomposition of fluctuations of GDP for each country at each point of time into their components, namely the global component, the regional component and the idiosyncratic component (the country specific component plus the residual term).

2.3.5.2 Path of the resilience of EEs

For each year of the sample period from 1991 to 2010, CAs were performed to compute the responses of EEs[71] to shocks spreading from AEs. Both the immediate effect

[71] 100,000 iterated simulations have been performed.

(“impact effect”), that is the effect felt at time $(t + 1)$ (the year after the shock), and the effect felt in each of the further subsequent three years, were computed. By summing the impact effect and that felt in the three years thereafter, we get what can be called the cumulated impact. Table 3.3 presents the median responses of EEs together with the lower and upper values (16th and the 84th percentiles, respectively) for different sub-samples of the whole period[72].

For the sub samples 1991-2000 and 2001-2010, the median immediate responses of all EEs, and the median cumulated responses, have also been plotted in Figure 3.6, panels 1 and 2. As one can see from Figure 3.6, the resilience of EEs was higher during the last ten years of the period than in the preceding ten years, both when the evaluation is made in terms of the immediate impact and when it is made in terms of the cumulated impact. During the period 2001-2010, for example, the cumulated impact resulting from the simulation has been about 15% lower than it has been in the period 1991-2000.

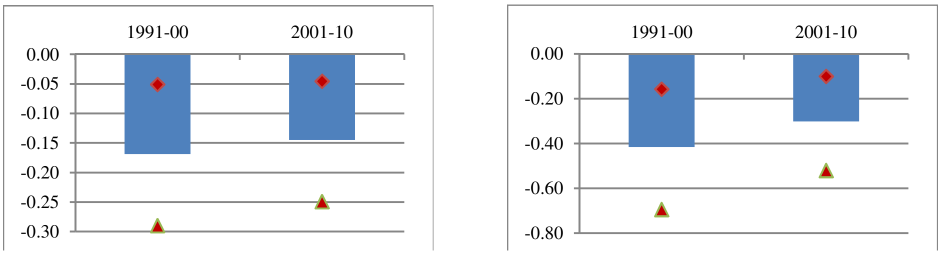
In other word, the simulated weaker economic dynamic in the AEs during the 2001-2010 period would have had a softer negative impact on the EEs than would the simulated weaker dynamic in the 1991-2000 period.

Table 3.3 Dynamic impact of the adverse scenario in AEs on all emerging economies

	t+1			*t+2*			*t+3*			*t+4*			Cumulated median impact		
	U	M	L	U	M	L	U	M	L	U	M	L	U	M	L
1991-2000	-0.05	-0.17	-0.29	-0.04	-0.09	-0.14	-0.04	-0.07	-0.12	-0.03	-0.08	-0.15	-0.16	-0.42	-0.70
2001-2010	-0.05	-0.15	-0.25	-0.03	-0.07	-0.11	-0.02	-0.04	-0.07	-0.01	-0.05	-0.09	-0.10	-0.30	-0.52
Subsamples															
1991-1995	-0.08	-0.20	-0.33	-0.03	-0.08	-0.14	-0.04	-0.08	-0.12	-0.05	-0.10	-0.16	-0.20	-0.47	-0.75
1996-2000	-0.03	-0.14	-0.25	-0.05	-0.09	-0.14	-0.03	-0.07	-0.12	-0.01	-0.06	-0.13	-0.11	-0.36	-0.64
2001-2005	-0.03	-0.13	-0.22	-0.03	-0.07	-0.11	0.00	-0.03	-0.06	0.03	-0.03	-0.08	-0.04	-0.25	-0.47
2006-2010	-0.06	-0.17	-0.28	-0.03	-0.07	-0.12	-0.03	-0.05	-0.09	-0.03	-0.06	-0.09	-0.14	-0.35	-0.57

Note: M stands for median, L and U stand for lower and upper values (16th and the 84th percentiles, respectively).

[72] Further results are available in appendix F.

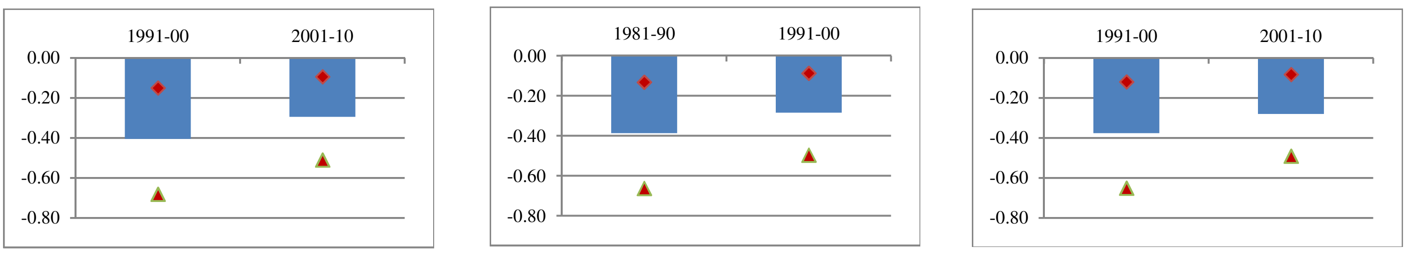


1. Immediate impact

2. Cumulated impact

Fig. 3.6 Impact (median, 16th and 84th percentiles) on EEs of shocks spreading from the AEs; ten year time windows

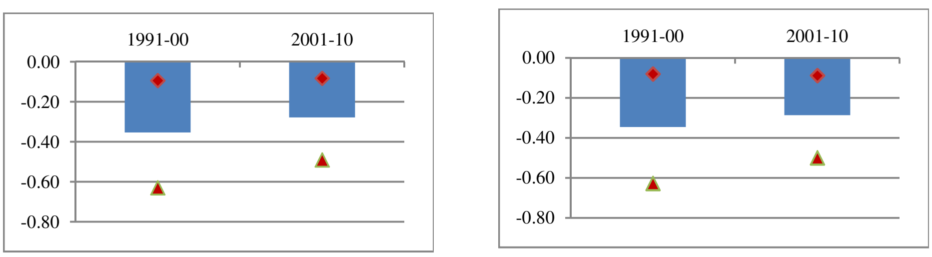
To assess whether the above results would reflect the behavior among the subsamples of EEs grouped by geographical areas, the above experiments were replicated for the EEs at geographical levels (namely Latin American, Asian, MENA, European, and SSA EEs). As with the entire group of EEs, the increasing resilience of EEs to adverse scenarios affecting AEs was observable, although certain regional peculiarities emerged. In fact, during the sub-sample 2001-2010 the magnitude of the cumulated impacts were estimated to be lower than the impact measured in the sub-sample 1991-2000 with percentages ranging from about 27% in Latin American EEs to 17% in SSA EEs for example (Figure 3.7, panels from 1 to 5, and Table 3.4).



1. Latin America EEs

2. Asia EEs

3. MENA EEs



4. Europe EEs

5. Sub Sahara Africa EEs

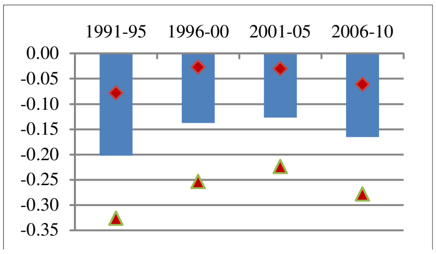
Fig. 3.7 Cumulated impact (median, 16th and 84th percentiles) on EEs (grouped by region) of shocks spreading from the AEs

Table 3.4 Dynamic impact of the adverse scenario in AEs on EEs grouped by regions

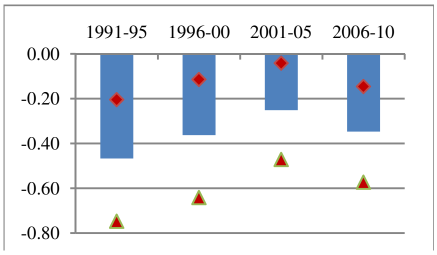
	t+1			*t+2*			*t+3*			*t+4*			Cumulated median impact		
	U	M	L	U	M	L	U	M	L	U	M	L	U	M	L
Latin America EEs															
1991-2000	-0.05	-0.16	-0.28	-0.04	-0.09	-0.14	-0.04	-0.07	-0.12	-0.03	-0.08	-0.14	-0.15	-0.40	-0.68
2001-2010	-0.04	-0.14	-0.24	-0.03	-0.07	-0.11	-0.01	-0.04	-0.07	-0.01	-0.05	-0.09	-0.09	-0.29	-0.51
Asia EEs															
1991-2000	-0.05	-0.17	-0.29	-0.04	-0.08	-0.14	-0.03	-0.07	-0.12	-0.01	-0.06	-0.12	-0.13	-0.39	-0.66
2001-2010	-0.05	-0.15	-0.25	-0.03	-0.07	-0.11	-0.01	-0.04	-0.06	0.00	-0.04	-0.07	-0.09	-0.28	-0.50
MENA EEs															
1991-2000	-0.05	-0.17	-0.29	-0.03	-0.08	-0.13	-0.03	-0.07	-0.11	-0.01	-0.06	-0.12	-0.12	-0.38	-0.65
2001-2010	-0.05	-0.15	-0.25	-0.03	-0.07	-0.11	-0.01	-0.04	-0.06	0.01	-0.03	-0.07	-0.08	-0.28	-0.49
Europe EEs															
1991-2000	-0.04	-0.15	-0.28	-0.03	-0.08	-0.13	-0.02	-0.06	-0.11	0.00	-0.06	-0.11	-0.09	-0.35	-0.63
2001-2010	-0.04	-0.14	-0.24	-0.03	-0.07	-0.11	-0.01	-0.03	-0.06	0.00	-0.03	-0.07	-0.08	-0.28	-0.49
Sub Sahara Africa EEs															
1991-2000	-0.02	-0.14	-0.27	-0.03	-0.08	-0.14	-0.01	-0.05	-0.09	-0.01	-0.07	-0.13	-0.08	-0.35	-0.63
2001-2010	-0.05	-0.14	-0.24	-0.03	-0.07	-0.11	-0.01	-0.03	-0.06	0.00	-0.04	-0.08	-0.09	-0.29	-0.50

Note: M stands for median, L and U stand for lower and upper values of the credible interval, respectively (16^{th} and the 84^{th} percentiles).

The whole sample period has also been broken down into smaller, five-year sub-samples, in order to obtain more detailed information on how the EEs' resilience evolved over time. A very interesting fact emerges here. If we observe the last ten years of the sample period, we see that the resilience of the EEs fell rather than rose during that period. The immediate impact (Figure 3.8, panel 1) measured during the five-year period 2006-2010 was 29% stronger than that measured in the previous five-year period (2001-2005). The same conclusions are reached if the results obtained for the cumulated impacts are considered (Figure 3.8, panel 2). Nevertheless if we extend the timeframe we see that, despite the increase in the intensity of impacts during the last ten years, the effect of the shock simulated in the five-year period 2006-2010 was lower than the impact in the five-year period 1991-1995 (about 15% and 25% in terms of immediate impact and cumulated impact, respectively). Therefore, the EEs' resilience (vulnerability) at the end of the 2000s is greater (smaller) than it was during the early 1990s.



1. Immediate impact



2. Cumulated impact

Fig. 3.8 Impact (median, 16th and 84th percentiles) on EEs of shocks spreading from the AEs; five year time windows

3. Conclusion

The decoupling hypothesis states that the degree of economic cycle interdependence between EEs and AEs has decreased in recent years. In investigating this hypothesis I followed two directions by studying: 1) the synchronicity of the economic cycles of EEs and AEs, and 2) the time path of resilience of EEs to adverse scenarios affecting AEs. The economic cycles of 112 countries (23 AEs, 59 EEs, and 30 DEs), covering more than 90% of the world's GDP (at PPP) and more than 85% of the world's population, were studied by two different tools for the empirical investigation: the Euclidean distance (for point 1) and the time-varying Panel VAR model (for point 2).

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, insofar as the degree of correlation between EEs and AEs may be determined by the decoupling phenomenon, there is no clear evidence of decoupling. However the point is that 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; so it was crucial to examine the decoupling hypothesis by attempting to measure how the influence of AEs on EEs has changed over time (the point 2 above), 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 then the specification with the group factors, and the results of the counterfactual analyses showed that, despite the fact that during the last ten years EEs became less resilient to external shocks, their degree of resilience is currently still higher than it was in the early 1990s.

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, country-specific components, and regional components too.

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 work discussed in this chapter by adding the credit variables in order to evaluate the decoupling phenomenon within the framework of international spillovers in macro-credit linkages; the next chapter will explore this point.

Appendix A. Set of Countries

Table A.1 Countries.

Advanced Economies	Emerging Economies		Developing Economies
Australia[g]	Albania[d]	Jamaica[b]	Bangladesh[c]
Austria[d]	Antigua[b]	Jordania[e]	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]
Finlandia[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 region 1[c]	Panama[b]	Gambia[f]
Japan[c]	China region 2[c]	Paraguay[b]	Ghana[f]
Luxembourg[d]	Colombia[b]	Perù[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]	Mauritiana[e]
Switzerland[d]	Gabon[f]	St. Kitss & 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. Main descriptive statistics

Table B1 Descriptive statistics of GDP growth rate (%) data for each country

Statistics on Series	Albania		
Annual Data From 197	0:01 To 2010:01		
Observations	40	Skipped/Missing	1
Sample Mean	2.379	Variance	53.893
Standard Error	7.341	of Sample Mean	1.161
t-Statistic (Mean=0)	2.050	Signif Level	0.047
Skewness	-1.765	Signif Level (Sk=0)	0.000
Kurtosis (excess)	6.197	Signif Level (Ku=0)	0.000
Jarque-Bera	84.783	Signif Level (JB=0)	0.000

Statistics on Series	Antigua		
Annual Data From 197	0:01 To 2010:01		
Observations	40	Skipped/Missing	1
Sample Mean	3.082	Variance	35.842
Standard Error	5.987	of Sample Mean	0.947
t-Statistic (Mean=0)	3.256	Signif Level	0.002
Skewness	-0.134	Signif Level (Sk=0)	0.739
Kurtosis (excess)	0.182	Signif Level (Ku=0)	0.830
Jarque-Bera	0.175	Signif Level (JB=0)	0.916

Statistics on Series	Argentina		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.338	Variance	22.711
Standard Error	4.766	of Sample Mean	0.744
t-Statistic (Mean=0)	1.798	Signif Level	0.080
Skewness	-0.499	Signif Level (Sk=0)	0.209
Kurtosis (excess)	-0.686	Signif Level (Ku=0)	0.411
Jarque-Bera	2.504	Signif Level (JB=0)	0.286

Statistics on Series	Australia		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.759	Variance	5.836
Standard Error	2.416	of Sample Mean	0.377
t-Statistic (Mean=0)	4.662	Signif Level	0.000
Skewness	-3.335	Signif Level (Sk=0)	0.000
Kurtosis (excess)	15.099	Signif Level (Ku=0)	0.000
Jarque-Bera	465.470	Signif Level (JB=0)	0.000

Statistics on Series	Austria		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	2.398	Variance	5.028
Standard Error	2.242	of Sample Mean	0.350
t-Statistic (Mean=0)	6.847	Signif Level	0.000
Skewness	-0.103	Signif Level (Sk=0)	0.796
Kurtosis (excess)	1.640	Signif Level (Ku=0)	0.050
Jarque-Bera	4.665	Signif Level (JB=0)	0.097

Statistics on Series	Bahamas		
Annual Data From 197	0:01 To 2010:01		
Observations	40	Skipped/Missing	1
Sample Mean	0.902	Variance	42.450
Standard Error	6.515	of Sample Mean	1.030
t-Statistic (Mean=0)	0.876	Signif Level	0.387
Skewness	-0.739	Signif Level (Sk=0)	0.066
Kurtosis (excess)	1.820	Signif Level (Ku=0)	0.032
Jarque-Bera	9.158	Signif Level (JB=0)	0.010

Statistics on Series	Malaysia		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	4.615	Variance	27.183
Standard Error	5.214	of Sample Mean	0.814
t-Statistic (Mean=0)	5.668	Signif Level	0.000
Skewness	-0.286	Signif Level (Sk=0)	0.472
Kurtosis (excess)	2.995	Signif Level (Ku=0)	0.000
Jarque-Bera	15.879	Signif Level (JB=0)	0.000

Statistics on Series	Mali		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	2.214	Variance	32.680
Standard Error	5.717	of Sample Mean	0.893
t-Statistic (Mean=0)	2.480	Signif Level	0.017
Skewness	0.163	Signif Level (Sk=0)	0.682
Kurtosis (excess)	0.270	Signif Level (Ku=0)	0.747
Jarque-Bera	0.305	Signif Level (JB=0)	0.858

Statistics on Series	Mauritiana		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.234	Variance	50.786
Standard Error	7.126	of Sample Mean	10.113
t-Statistic (Mean=0)	1.109	Signif Level	0.274
Skewness	0.447	Signif Level (Sk=0)	0.260
Kurtosis (excess)	1.077	Signif Level (Ku=0)	0.197
Jarque-Bera	3.347	Signif Level (JB=0)	0.188

Statistics on Series	Mauritius		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	4.073	Variance	30.293
Standard Error	5.504	of Sample Mean	0.860
t-Statistic (Mean=0)	4.738	Signif Level	0.000
Skewness	-0.390	Signif Level (Sk=0)	0.326
Kurtosis (excess)	4.635	Signif Level (Ku=0)	0.000
Jarque-Bera	37.737	Signif Level (JB=0)	0.000

Statistics on Series	India		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	3.403	Variance	10.637
Standard Error	3.261	of Sample Mean	0.509
t-Statistic (Mean=0)	6.681	Signif Level	0.000
Skewness	-0.049	Signif Level (Sk=0)	0.902
Kurtosis (excess)	-0.200	Signif Level (Ku=0)	0.811
Jarque-Bera	0.085	Signif Level (JB=0)	0.959

Statistics on Series	Indonesia		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	4.200	Variance	15.6405
Standard Error	3.955	of Sample Mean	0.618
t-Statistic (Mean=0)	6.800	Signif Level	0.000
Skewness	-2.560	Signif Level (Sk=0)	0.000
Kurtosis (excess)	11.905	Signif Level (Ku=0)	0.000
Jarque-Bera	286.913	Signif Level (JB=0)	0.000

Table B1 Continue

Statistics on Series	Bahrain		
Annual Data From 197	0:01 To 2010:01		
Observations	40	Skipped/Missing	1
Sample Mean	0.484	Variance	69.943
Standard Error	8.363	of Sample Mean	1.322
t-Statistic (Mean=0)	0.366	Signif Level	0.716
Skewness	0.248	Signif Level (Sk=0)	0.538
Kurtosis (excess)	5.324	Signif Level (Ku=0)	0.000
Jarque-Bera	47.652	Signif Level (JB=0)	0.000

Statistics on Series	Bangladesh		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.709	Variance	13.978
Standard Error	3.739	of Sample Mean	0.584
t-Statistic (Mean=0)	2.928	Signif Level	0.006
Skewness	-1.589	Signif Level (Sk=0)	0.000
Kurtosis (excess)	3.981	Signif Level (Ku=0)	0.000
Jarque-Bera	44.343	Signif Level (JB=0)	0.000

Statistics on Series	Barbados		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	0.473	Variance	25.000
Standard Error	5.000	of Sample Mean	0.781
t-Statistic (Mean=0)	0.605	Signif Level	0.549
Skewness	-0.191	Signif Level (Sk=0)	0.630
Kurtosis (excess)	0.143	Signif Level (Ku=0)	0.864
Jarque-Bera	0.284	Signif Level (JB=0)	0.867

Statistics on Series	Belgium		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	2.189	Variance	5.340
Standard Error	2.311	of Sample Mean	0.361
t-Statistic (Mean=0)	6.065	Signif Level	0.000
Skewness	-0.407	Signif Level (Sk=0)	0.305
Kurtosis (excess)	0.518	Signif Level (Ku=0)	0.535
Jarque-Bera	1.592	Signif Level (JB=0)	0.451

Statistics on Series	Canada		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.870	Variance	5.485
Standard Error	2.342	of Sample Mean	0.366
t-Statistic (Mean=0)	5.112	Signif Level	0.000
Skewness	-1.045	Signif Level (Sk=0)	0.008
Kurtosis (excess)	1.352	Signif Level (Ku=0)	0.105
Jarque-Bera	10.589	Signif Level (JB=0)	0.005

Statistics on Series	Chile		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	2.750	Variance	36.457
Standard Error	6.038	of Sample Mean	0.943
t-Statistic (Mean=0)	2.917	Signif Level	0.006
Skewness	-1.813	Signif Level (Sk=0)	0.000
Kurtosis (excess)	3.978	Signif Level (Ku=0)	0.000
Jarque-Bera	49.479	Signif Level (JB=0)	0.000

Statistics on Series	Iran		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	0.981	Variance	75.700
Standard Error	8.701	of Sample Mean	1.359
t-Statistic (Mean=0)	0.722	Signif Level	0.474
Skewness	-0.471	Signif Level (Sk=0)	0.235
Kurtosis (excess)	-0.143	Signif Level (Ku=0)	0.864
Jarque-Bera	1.552	Signif Level (JB=0)	0.460

Statistics on Series	Ireland		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	2.995	Variance	20.569
Standard Error	4.535	of Sample Mean	0.708
t-Statistic (Mean=0)	4.228	Signif Level	0.000
Skewness	-0.565	Signif Level (Sk=0)	0.155
Kurtosis (excess)	0.788	Signif Level (Ku=0)	0.345
Jarque-Bera	3.245	Signif Level (JB=0)	0.197

Statistics on Series	Israel		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	2.016	Variance	9.125
Standard Error	3.021	of Sample Mean	0.472
t-Statistic (Mean=0)	4.273	Signif Level	0.000
Skewness	-0.213	Signif Level (Sk=0)	0.592
Kurtosis (excess)	-0.426	Signif Level (Ku=0)	0.610
Jarque-Bera	0.620	Signif Level (JB=0)	0.734

Statistics on Series	Italy		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.844	Variance	7.005
Standard Error	2.647	of Sample Mean	0.413
t-Statistic (Mean=0)	4.462	Signif Level	0.000
Skewness	-0.661	Signif Level (Sk=0)	0.096
Kurtosis (excess)	1.873	Signif Level (Ku=0)	0.025
Jarque-Bera	8.975	Signif Level (JB=0)	0.011

Statistics on Series	Jamaica		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	0.376	Variance	15.594
Standard Error	3.949	of Sample Mean	0.617
t-Statistic (Mean=0)	0.610	Signif Level	0.545
Skewness	0.995	Signif Level (Sk=0)	0.012
Kurtosis (excess)	1.660	Signif Level (Ku=0)	0.047
Jarque-Bera	11.474	Signif Level (JB=0)	0.003

Statistics on Series	Japan		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	2.309	Variance	9.036
Standard Error	3.006	of Sample Mean	0.469
t-Statistic (Mean=0)	4.919	Signif Level	0.000
Skewness	-0.401	Signif Level (Sk=0)	0.312
Kurtosis (excess)	1.775	Signif Level (Ku=0)	0.034
Jarque-Bera	6.480	Signif Level (JB=0)	0.039

Table B1 Continue

Statistics on Series	China ver1		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	7.966	Variance	22.679
Standard Error	4.762	of Sample Mean	0.744
t-Statistic (Mean=0)	10.711	Signif Level	0.000
Skewness	0.376	Signif Level (Sk=0)	0.344
Kurtosis (excess)	2.951	Signif Level (Ku=0)	0.000
Jarque-Bera	15.848	Signif Level (JB=0)	0.000

Statistics on Series	China ver2		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	5.991	Variance	16.558
Standard Error	4.069	of Sample Mean	0.635
t-Statistic (Mean=0)	9.428	Signif Level	0.000
Skewness	-0.394	Signif Level (Sk=0)	0.321
Kurtosis (excess)	0.022	Signif Level (Ku=0)	0.979
Jarque-Bera	1.064	Signif Level (JB=0)	0.587

Statistics on Series	Colombia		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.903	Variance	5.840
Standard Error	2.417	of Sample Mean	0.377
t-Statistic (Mean=0)	5.043	Signif Level	0.000
Skewness	-1.080	Signif Level (Sk=0)	0.007
Kurtosis (excess)	2.638	Signif Level (Ku=0)	0.002
Jarque-Bera	19.849	Signif Level (JB=0)	0.000

Statistics on Series	Congo Rep		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.706	Variance	59.122
Standard Error	7.689	of Sample Mean	10.201
t-Statistic (Mean=0)	1.421	Signif Level	0.163
Skewness	0.370	Signif Level (Sk=0)	0.351
Kurtosis (excess)	1.083	Signif Level (Ku=0)	0.195
Jarque-Bera	2.940	Signif Level (JB=0)	0.230

Statistics on Series	Costa Rica		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.625	Variance	12.323
Standard Error	3.510	of Sample Mean	0.548
t-Statistic (Mean=0)	2.965	Signif Level	0.005
Skewness	-1.441	Signif Level (Sk=0)	0.000
Kurtosis (excess)	3.444	Signif Level (Ku=0)	0.000
Jarque-Bera	34.453	Signif Level (JB=0)	0.000

Statistics on Series	Cote d'Ivoire		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	-0.043	Variance	16.852
Standard Error	4.105	of Sample Mean	0.641
t-Statistic (Mean=0)	-0.067	Signif Level	0.947
Skewness	-0.225	Signif Level (Sk=0)	0.571
Kurtosis (excess)	1.800	Signif Level (Ku=0)	0.031
Jarque-Bera	5.883	Signif Level (JB=0)	0.053

Statistics on Series	Jordania		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.110	Variance	50.281
Standard Error	7.091	of Sample Mean	1.107
t-Statistic (Mean=0)	1.002	Signif Level	0.322
Skewness	-0.333	Signif Level (Sk=0)	0.402
Kurtosis (excess)	0.516	Signif Level (Ku=0)	0.537
Jarque-Bera	1.213	Signif Level (JB=0)	0.545

Statistics on Series	Kenia		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	0.299	Variance	13.311
Standard Error	3.648	of Sample Mean	0.570
t-Statistic (Mean=0)	0.525	Signif Level	0.603
Skewness	-0.234	Signif Level (Sk=0)	0.556
Kurtosis (excess)	0.393	Signif Level (Ku=0)	0.638
Jarque-Bera	0.636	Signif Level (JB=0)	0.728

Statistics on Series	Mexico		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.533	Variance	17.971
Standard Error	4.239	of Sample Mean	0.662
t-Statistic (Mean=0)	2.316	Signif Level	0.026
Skewness	-1.211	Signif Level (Sk=0)	0.002
Kurtosis (excess)	1.222	Signif Level (Ku=0)	0.143
Jarque-Bera	12.569	Signif Level (JB=0)	0.002

Statistics on Series	Morocco		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	2.427	Variance	29.770
Standard Error	5.456	of Sample Mean	0.852
t-Statistic (Mean=0)	2.848	Signif Level	0.007
Skewness	0.313	Signif Level (Sk=0)	0.431
Kurtosis (excess)	1.272	Signif Level (Ku=0)	0.128
Jarque-Bera	3.433	Signif Level (JB=0)	0.180

Statistics on Series	Nepal		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.764	Variance	11.063
Standard Error	3.326	of Sample Mean	0.519
t-Statistic (Mean=0)	3.396	Signif Level	0.002
Skewness	0.092	Signif Level (Sk=0)	0.816
Kurtosis (excess)	0.371	Signif Level (Ku=0)	0.657
Jarque-Bera	0.293	Signif Level (JB=0)	0.864

Statistics on Series	Netherlands		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.786	Variance	4.182
Standard Error	2.045	of Sample Mean	0.319
t-Statistic (Mean=0)	5.594	Signif Level	0.000
Skewness	-1.197	Signif Level (Sk=0)	0.003
Kurtosis (excess)	2.047	Signif Level (Ku=0)	0.014
Jarque-Bera	16.953	Signif Level (JB=0)	0.000

Table B1 Continue

Statistics on Series	Denmark		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.653	Variance	6.269
Standard Error	2.504	of Sample Mean	0.391
t-Statistic (Mean=0)	4.227	Signif Level	0.000
Skewness	-0.704	Signif Level (Sk=0)	0.076
Kurtosis (excess)	2.394	Signif Level (Ku=0)	0.004
Jarque-Bera	13.178	Signif Level (JB=0)	0.001

Statistics on Series	Dominica		
Annual Data From 197	0:01 To 2010:01		
Observations	40	Skipped/Missing	1
Sample Mean	3.575	Variance	20.874
Standard Error	4.569	of Sample Mean	0.722
t-Statistic (Mean=0)	4.949	Signif Level	0.000
Skewness	-0.774	Signif Level (Sk=0)	0.054
Kurtosis (excess)	2.801	Signif Level (Ku=0)	0.001
Jarque-Bera	17.079	Signif Level (JB=0)	0.000

Statistics on Series	Belize		
Annual Data From 197	0:01 To 2010:01		
Observations	40	Skipped/Missing	1
Sample Mean	2.152	Variance	22.239
Standard Error	4.716	of Sample Mean	0.746
t-Statistic (Mean=0)	2.886	Signif Level	0.006
Skewness	0.370	Signif Level (Sk=0)	0.358
Kurtosis (excess)	-0.847	Signif Level (Ku=0)	0.317
Jarque-Bera	2.109	Signif Level (JB=0)	0.348

Statistics on Series	Benin		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	0.995	Variance	31.390
Standard Error	5.603	of Sample Mean	0.875
t-Statistic (Mean=0)	1.137	Signif Level	0.262
Skewness	1.280	Signif Level (Sk=0)	0.001
Kurtosis (excess)	5.252	Signif Level (Ku=0)	0.000
Jarque-Bera	58.318	Signif Level (JB=0)	0.000

Statistics on Series	Bermuda		
Annual Data From 197	0:01 To 2010:01		
Observations	40	Skipped/Missing	1
Sample Mean	1.655	Variance	20.744
Standard Error	4.555	of Sample Mean	0.720
t-Statistic (Mean=0)	2.298	Signif Level	0.027
Skewness	1.671	Signif Level (Sk=0)	0.000
Kurtosis (excess)	8.620	Signif Level (Ku=0)	0.000
Jarque-Bera	142.451	Signif Level (JB=0)	0.000

Statistics on Series	Bolivia		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	0.758	Variance	6.584
Standard Error	2.566	of Sample Mean	0.401
t-Statistic (Mean=0)	1.890	Signif Level	0.066
Skewness	-1.116	Signif Level (Sk=0)	0.005
Kurtosis (excess)	1.202	Signif Level (Ku=0)	0.150
Jarque-Bera	10.986	Signif Level (JB=0)	0.004

Statistics on Series	New Zealand		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.209	Variance	5.264
Standard Error	2.294	of Sample Mean	0.358
t-Statistic (Mean=0)	3.374	Signif Level	0.002
Skewness	-0.571	Signif Level (Sk=0)	0.151
Kurtosis (excess)	0.460	Signif Level (Ku=0)	0.581
Jarque-Bera	2.586	Signif Level (JB=0)	0.274

Statistics on Series	Nicaragua		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	-0.648	Variance	81.479
Standard Error	9.027	of Sample Mean	1.410
t-Statistic (Mean=0)	-0.460	Signif Level	0.648
Skewness	-1.247	Signif Level (Sk=0)	0.002
Kurtosis (excess)	10.054	Signif Level (Ku=0)	0.000
Jarque-Bera	183.305	Signif Level (JB=0)	0.000

Statistics on Series	Nigeria		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	0.965	Variance	61.395
Standard Error	7.836	of Sample Mean	10.224
t-Statistic (Mean=0)	0.788	Signif Level	0.435
Skewness	0.392	Signif Level (Sk=0)	0.324
Kurtosis (excess)	0.173	Signif Level (Ku=0)	0.836
Jarque-Bera	1.099	Signif Level (JB=0)	0.577

Statistics on Series	Norway		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	2.651	Variance	4.116
Standard Error	2.029	of Sample Mean	0.317
t-Statistic (Mean=0)	8.368	Signif Level	0.000
Skewness	-0.217	Signif Level (Sk=0)	0.585
Kurtosis (excess)	-0.530	Signif Level (Ku=0)	0.526
Jarque-Bera	0.800	Signif Level (JB=0)	0.670

Statistics on Series	Oman		
Annual Data From 197	0:01 To 2010:01		
Observations	40	Skipped/Missing	1
Sample Mean	3.664	Variance	79.888
Standard Error	8.938	of Sample Mean	1.413
t-Statistic (Mean=0)	2.592	Signif Level	0.013
Skewness	0.875	Signif Level (Sk=0)	0.030
Kurtosis (excess)	4.085	Signif Level (Ku=0)	0.000
Jarque-Bera	32.906	Signif Level (JB=0)	0.000

Statistics on Series	Pakistan		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	2.487	Variance	7.753
Standard Error	2.784	of Sample Mean	0.435
t-Statistic (Mean=0)	5.720	Signif Level	0.000
Skewness	1.612	Signif Level (Sk=0)	0.000
Kurtosis (excess)	4.641	Signif Level (Ku=0)	0.000
Jarque-Bera	54.554	Signif Level (JB=0)	0.000

Table B1 Continue

Statistics on Series	Botswana		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	5.816	Variance	73.936
Standard Error	8.599	of Sample Mean	1.343
t-Statistic (Mean=0)	4.331	Signif Level	0.000
Skewness	0.915	Signif Level (Sk=0)	0.021
Kurtosis (excess)	1.597	Signif Level (Ku=0)	0.056
Jarque-Bera	10.077	Signif Level (JB=0)	0.006

Statistics on Series	Brazil		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	2.179	Variance	18.729
Standard Error	4.328	of Sample Mean	0.676
t-Statistic (Mean=0)	3.224	Signif Level	0.003
Skewness	0.006	Signif Level (Sk=0)	0.988
Kurtosis (excess)	0.033	Signif Level (Ku=0)	0.968
Jarque-Bera	0.002	Signif Level (JB=0)	0.999

Statistics on Series	Bulgaria		
Annual Data From 197	0:01 To 2010:01		
Observations	40	Skipped/Missing	1
Sample Mean	3.504	Variance	22.177
Standard Error	4.709	of Sample Mean	0.745
t-Statistic (Mean=0)	4.706	Signif Level	0.000
Skewness	-1.150	Signif Level (Sk=0)	0.004
Kurtosis (excess)	0.512	Signif Level (Ku=0)	0.546
Jarque-Bera	9.258	Signif Level (JB=0)	0.010

Statistics on Series	Burkina Faso		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.596	Variance	24.169
Standard Error	4.916	of Sample Mean	0.768
t-Statistic (Mean=0)	2.079	Signif Level	0.044
Skewness	1.380	Signif Level (Sk=0)	0.001
Kurtosis (excess)	5.386	Signif Level (Ku=0)	0.000
Jarque-Bera	62.576	Signif Level (JB=0)	0.000

Statistics on Series	Burundi		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	0.409	Variance	33.591
Standard Error	5.796	of Sample Mean	0.905
t-Statistic (Mean=0)	0.452	Signif Level	0.654
Skewness	1.197	Signif Level (Sk=0)	0.003
Kurtosis (excess)	5.888	Signif Level (Ku=0)	0.000
Jarque-Bera	69.006	Signif Level (JB=0)	0.000

Statistics on Series	Cameroon		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	0.612	Variance	29.900
Standard Error	5.468	of Sample Mean	0.854
t-Statistic (Mean=0)	0.716	Signif Level	0.478
Skewness	0.685	Signif Level (Sk=0)	0.084
Kurtosis (excess)	1.593	Signif Level (Ku=0)	0.056
Jarque-Bera	7.544	Signif Level (JB=0)	0.023

Statistics on Series	Panama		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	3.073	Variance	24.964
Standard Error	4.996	of Sample Mean	0.780
t-Statistic (Mean=0)	3.938	Signif Level	0.000
Skewness	0.756	Signif Level (Sk=0)	0.057
Kurtosis (excess)	3.148	Signif Level (Ku=0)	0.000
Jarque-Bera	20.843	Signif Level (JB=0)	0.000

Statistics on Series	Paraguay		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.823	Variance	19.274
Standard Error	4.390	of Sample Mean	0.686
t-Statistic (Mean=0)	2.658	Signif Level	0.011
Skewness	0.839	Signif Level (Sk=0)	0.035
Kurtosis (excess)	1.335	Signif Level (Ku=0)	0.110
Jarque-Bera	7.852	Signif Level (JB=0)	0.020

Statistics on Series	Perù		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.282	Variance	33.946
Standard Error	5.826	of Sample Mean	0.910
t-Statistic (Mean=0)	1.408	Signif Level	0.167
Skewness	-1.119	Signif Level (Sk=0)	0.005
Kurtosis (excess)	1.889	Signif Level (Ku=0)	0.024
Jarque-Bera	14.656	Signif Level (JB=0)	0.001

Statistics on Series	Philippines		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.553	Variance	13.229
Standard Error	3.637	of Sample Mean	0.568
t-Statistic (Mean=0)	2.734	Signif Level	0.009
Skewness	-1.692	Signif Level (Sk=0)	0.000
Kurtosis (excess)	3.891	Signif Level (Ku=0)	0.000
Jarque-Bera	45.430	Signif Level (JB=0)	0.000

Statistics on Series	Poland		
Annual Data From 197	0:01 To 2010:01		
Observations	40	Skipped/Missing	1
Sample Mean	2.692	Variance	20.149
Standard Error	4.489	of Sample Mean	0.710
t-Statistic (Mean=0)	3.793	Signif Level	0.001
Skewness	-2.045	Signif Level (Sk=0)	0.000
Kurtosis (excess)	3.866	Signif Level (Ku=0)	0.000
Jarque-Bera	52.801	Signif Level (JB=0)	0.000

Statistics on Series	Portugal		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	2.615	Variance	18.990
Standard Error	4.358	of Sample Mean	0.681
t-Statistic (Mean=0)	3.842	Signif Level	0.000
Skewness	-0.682	Signif Level (Sk=0)	0.086
Kurtosis (excess)	2.445	Signif Level (Ku=0)	0.003
Jarque-Bera	13.387	Signif Level (JB=0)	0.001

Table B1 Continue

Statistics on Series	Dominican Rep		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	3.605	Variance	19.534
Standard Error	4.420	of Sample Mean	0.690
t-Statistic (Mean=0)	5.223	Signif Level	0.000
Skewness	-0.065	Signif Level (Sk=0)	0.871
Kurtosis (excess)	-0.244	Signif Level (Ku=0)	0.770
Jarque-Bera	0.130	Signif Level (JB=0)	0.937

Statistics on Series	Ecuador		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	2.054	Variance	20.345
Standard Error	4.510	of Sample Mean	0.704
t-Statistic (Mean=0)	2.915	Signif Level	0.006
Skewness	0.175	Signif Level (Sk=0)	0.659
Kurtosis (excess)	3.676	Signif Level (Ku=0)	0.000
Jarque-Bera	23.294	Signif Level (JB=0)	0.000

Statistics on Series	Egypt		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	3.685	Variance	18.164
Standard Error	4.262	of Sample Mean	0.666
t-Statistic (Mean=0)	5.537	Signif Level	0.000
Skewness	1.297	Signif Level (Sk=0)	0.001
Kurtosis (excess)	4.080	Signif Level (Ku=0)	0.000
Jarque-Bera	39.941	Signif Level (JB=0)	0.000

Statistics on Series	El Salvador		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.086	Variance	12.300
Standard Error	3.507	of Sample Mean	0.548
t-Statistic (Mean=0)	1.983	Signif Level	0.054
Skewness	-1.262	Signif Level (Sk=0)	0.001
Kurtosis (excess)	1.865	Signif Level (Ku=0)	0.026
Jarque-Bera	16.823	Signif Level (JB=0)	0.000

Statistics on Series	Ethiopia		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.147	Variance	53.074
Standard Error	7.285	of Sample Mean	1.138
t-Statistic (Mean=0)	1.008	Signif Level	0.320
Skewness	0.676	Signif Level (Sk=0)	0.089
Kurtosis (excess)	3.268	Signif Level (Ku=0)	0.000
Jarque-Bera	21.367	Signif Level (JB=0)	0.000

Statistics on Series	Fiji			
Annual Data From 197	0:01 To 2010:01			
Observations	41			
Sample Mean	1.536	Variance	2	25.426
Standard Error	5.042	of Sample Mean		0.787
t-Statistic (Mean=0)	1.950	Signif Level		0.058
Skewness	0.446	Signif Level (Sk=0)		0.262
Kurtosis (excess)	0.073	Signif Level (Ku=0)		0.930
Jarque-Bera	1.365	Signif Level (JB=0)		0.505

Statistics on Series	Romania		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	3.248	Variance	39.857
Standard Error	6.313	of Sample Mean	0.986
t-Statistic (Mean=0)	3.294	Signif Level	0.002
Skewness	-0.585	Signif Level (Sk=0)	0.141
Kurtosis (excess)	0.449	Signif Level (Ku=0)	0.591
Jarque-Bera	2.682	Signif Level (JB=0)	0.262

Statistics on Series	Rwanda		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	2.334	Variance	313.235
Standard Error	17.698	of Sample Mean	2.764
t-Statistic (Mean=0)	0.845	Signif Level	0.403
Skewness	1.770	Signif Level (Sk=0)	0.000
Kurtosis (excess)	12.402	Signif Level (Ku=0)	0.000
Jarque-Bera	284.161	Signif Level (JB=0)	0.000

Statistics on Series	Sierra Leone		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.127	Variance	62.130
Standard Error	7.882	of Sample Mean	1.231
t-Statistic (Mean=0)	0.915	Signif Level	0.365
Skewness	-0.809	Signif Level (Sk=0)	0.042
Kurtosis (excess)	2.376	Signif Level (Ku=0)	0.004
Jarque-Bera	14.123	Signif Level (JB=0)	0.001

Statistics on Series	Singapore		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	5.543	Variance	23.581
Standard Error	4.856	of Sample Mean	0.758
t-Statistic (Mean=0)	7.309	Signif Level	0.000
Skewness	-0.714	Signif Level (Sk=0)	0.072
Kurtosis (excess)	0.369	Signif Level (Ku=0)	0.658
Jarque-Bera	3.717	Signif Level (JB=0)	0.156

Statistics on Series	South Africa		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.016	Variance	7.662
Standard Error	2.768	of Sample Mean	0.432
t-Statistic (Mean=0)	2.350	Signif Level	0.024
Skewness	-0.413	Signif Level (Sk=0)	0.298
Kurtosis (excess)	0.152	Signif Level (Ku=0)	0.856
Jarque-Bera	1.207	Signif Level (JB=0)	0.547

Statistics on Series	Spain		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	2.098	Variance	6.428
Standard Error	2.535	of Sample Mean	0.396
t-Statistic (Mean=0)	5.298	Signif Level	0.000
Skewness	-0.121	Signif Level (Sk=0)	0.760
Kurtosis (excess)	0.879	Signif Level (Ku=0)	0.292
Jarque-Bera	1.422	Signif Level (JB=0)	0.491

Table B1 Continue

Statistics on Series	Finlandia		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	2.412	Variance	15.224
Standard Error	3.902	of Sample Mean	0.609
t-Statistic (Mean=0)	3.958	Signif Level	0.000
Skewness	-1.481	Signif Level (Sk=0)	0.000
Kurtosis (excess)	2.899	Signif Level (Ku=0)	0.001
Jarque-Bera	29.338	Signif Level (JB=0)	0.000

Statistics on Series	France		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.792	Variance	3.579
Standard Error	1.892	of Sample Mean	0.295
t-Statistic (Mean=0)	6.067	Signif Level	0.000
Skewness	-0.481	Signif Level (Sk=0)	0.226
Kurtosis (excess)	0.704	Signif Level (Ku=0)	0.399
Jarque-Bera	2.425	Signif Level (JB=0)	0.297

Statistics on Series	Gabon		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.076	Variance	105.062
Standard Error	10.250	of Sample Mean	1.601
t-Statistic (Mean=0)	0.672	Signif Level	0.505
Skewness	0.634	Signif Level (Sk=0)	0.110
Kurtosis (excess)	3.657	Signif Level (Ku=0)	0.000
Jarque-Bera	25.587	Signif Level (JB=0)	0.000

Statistics on Series	Gambia		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	0.089	Variance	20.798
Standard Error	4.560	of Sample Mean	0.712
t-Statistic (Mean=0)	0.125	Signif Level	0.901
Skewness	0.289	Signif Level (Sk=0)	0.467
Kurtosis (excess)	0.958	Signif Level (Ku=0)	0.251
Jarque-Bera	2.140	Signif Level (JB=0)	0.343

Statistics on Series	Germany		
Annual Data From 197	0:01 To 2010:01		
Observations	40	Skipped/Missing	1
Sample Mean	1.854	Variance	4.280
Standard Error	2.069	of Sample Mean	0.327
t-Statistic (Mean=0)	5.667	Signif Level	0.000
Skewness	-1.097	Signif Level (Sk=0)	0.006
Kurtosis (excess)	2.502	Signif Level (Ku=0)	0.003
Jarque-Bera	18.446	Signif Level (JB=0)	0.000

Statistics on Series	Ghana		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.398	Variance	30.862
Standard Error	5.555	of Sample Mean	0.868
t-Statistic (Mean=0)	1.611	Signif Level	0.115
Skewness	0.285	Signif Level (Sk=0)	0.473
Kurtosis (excess)	4.774	Signif Level (Ku=0)	0.000
Jarque-Bera	39.496	Signif Level (JB=0)	0.000

Statistics on Series	Sri Lanka		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	4.038	Variance	14.672
Standard Error	3.830	of Sample Mean	0.598
t-Statistic (Mean=0)	6.749	Signif Level	0.000
Skewness	0.868	Signif Level (Sk=0)	0.029
Kurtosis (excess)	2.705	Signif Level (Ku=0)	0.001
Jarque-Bera	17.648	Signif Level (JB=0)	0.000

Statistics on Series	St. Kitss & Nevis		
Annual Data From 197	0:01 To 2010:01		
Observations	40	Skipped/Missing	1
Sample Mean	4.204	Variance	21.010
Standard Error	4.584	of Sample Mean	0.725
t-Statistic (Mean=0)	5.800	Signif Level	0.000
Skewness	-0.856	Signif Level (Sk=0)	0.033
Kurtosis (excess)	1.275	Signif Level (Ku=0)	0.132
Jarque-Bera	7.594	Signif Level (JB=0)	0.022

Statistics on Series	St. Lucia		
Annual Data From 197	0:01 To 2010:01		
Observations	40	Skipped/Missing	1
Sample Mean	3.150	Variance	27.932
Standard Error	5.285	of Sample Mean	0.836
t-Statistic (Mean=0)	3.769	Signif Level	0.001
Skewness	0.869	Signif Level (Sk=0)	0.031
Kurtosis (excess)	0.738	Signif Level (Ku=0)	0.384
Jarque-Bera	5.939	Signif Level (JB=0)	0.051

Statistics on Series	St. Vincent & Granadine		
Annual Data From 197	0:01 To 2010:01		
Observations	40	Skipped/Missing	1
Sample Mean	3.297	Variance	37.786
Standard Error	6.147	of Sample Mean	0.972
t-Statistic (Mean=0)	3.392	Signif Level	0.002
Skewness	0.265	Signif Level (Sk=0)	0.511
Kurtosis (excess)	3.337	Signif Level (Ku=0)	0.000
Jarque-Bera	19.026	Signif Level (JB=0)	0.000

Statistics on Series	Swaziland		
Annual Data From 197	0:01 To 2010:01		
Observations	40	Skipped/Missing	1
Sample Mean	2.914	Variance	107.760
Standard Error	10.381	of Sample Mean	1.641
t-Statistic (Mean=0)	1.776	Signif Level	0.084
Skewness	2.751	Signif Level (Sk=0)	0.000
Kurtosis (excess)	10.093	Signif Level (Ku=0)	0.000
Jarque-Bera	220.248	Signif Level (JB=0)	0.000

Statistics on Series	Sweden		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.555	Variance	5.622
Standard Error	2.371	of Sample Mean	0.370
t-Statistic (Mean=0)	4.199	Signif Level	0.000
Skewness	-0.952	Signif Level (Sk=0)	0.016
Kurtosis (excess)	0.667	Signif Level (Ku=0)	0.425
Jarque-Bera	6.958	Signif Level (JB=0)	0.031

Table B1 Continue

Statistics on Series	Greece		
Annual Data From 1970:01 To 2010:01			
Observations	41		
Sample Mean	2.065	Variance	14.517
Standard Error	3.810	of Sample Mean	0.595
t-Statistic (Mean=0)	3.470	Signif Level	0.001
Skewness	-0.314	Signif Level (Sk=0)	0.428
Kurtosis (excess)	0.249	Signif Level (Ku=0)	0.766
Jarque-Bera	0.781	Signif Level (JB=0)	0.677

Statistics on Series	Grenada		
Annual Data From 1970:01 To 2010:01			
Observations	40	Skipped/Missing	1
Sample Mean	4.279	Variance	36.678
Standard Error	6.056	of Sample Mean	0.958
t-Statistic (Mean=0)	4.469	Signif Level	0.000
Skewness	0.813	Signif Level (Sk=0)	0.043
Kurtosis (excess)	3.783	Signif Level (Ku=0)	0.000
Jarque-Bera	28.266	Signif Level (JB=0)	0.000

Statistics on Series	Guatemala		
Annual Data From 1970:01 To 2010:01			
Observations	41		
Sample Mean	1.142	Variance	6.093
Standard Error	2.468	of Sample Mean	0.385
t-Statistic (Mean=0)	2.963	Signif Level	0.005
Skewness	-0.333	Signif Level (Sk=0)	0.402
Kurtosis (excess)	0.166	Signif Level (Ku=0)	0.842
Jarque-Bera	0.804	Signif Level (JB=0)	0.669

Statistics on Series	Guinea		
Annual Data From 1970:01 To 2010:01			
Observations	41		
Sample Mean	0.028	Variance	11.051
Standard Error	3.324	of Sample Mean	0.519
t-Statistic (Mean=0)	0.054	Signif Level	0.958
Skewness	-1.562	Signif Level (Sk=0)	0.000
Kurtosis (excess)	5.398	Signif Level (Ku=0)	0.000
Jarque-Bera	66.443	Signif Level (JB=0)	0.000

Statistics on Series	Honduras		
Annual Data From 1970:01 To 2010:01			
Observations	41		
Sample Mean	1.094	Variance	13.516
Standard Error	3.676	of Sample Mean	0.574
t-Statistic (Mean=0)	1.905	Signif Level	0.064
Skewness	-0.400	Signif Level (Sk=0)	0.313
Kurtosis (excess)	-0.038	Signif Level (Ku=0)	0.964
Jarque-Bera	1.098	Signif Level (JB=0)	0.577

Statistics on Series	Hong Kong		
Annual Data From 1970:01 To 2010:01			
Observations	41		
Sample Mean	4.551	Variance	17.989
Standard Error	4.241	of Sample Mean	0.662
t-Statistic (Mean=0)	6.870	Signif Level	0.000
Skewness	-0.451	Signif Level (Sk=0)	0.256
Kurtosis (excess)	0.190	Signif Level (Ku=0)	0.820
Jarque-Bera	1.451	Signif Level (JB=0)	0.484

Statistics on Series	Switzerland		
Annual Data From 1970:01 To 2010:01			
Observations	41		
Sample Mean	0.937	Variance	6.361
Standard Error	2.522	of Sample Mean	0.394
t-Statistic (Mean=0)	2.380	Signif Level	0.022
Skewness	-1.472	Signif Level (Sk=0)	0.000
Kurtosis (excess)	5.414	Signif Level (Ku=0)	0.000
Jarque-Bera	64.891	Signif Level (JB=0)	0.000

Statistics on Series	Syria		
Annual Data From 1970:01 To 2010:01			
Observations	41		
Sample Mean	1.796	Variance	62.646
Standard Error	7.915	of Sample Mean	1.236
t-Statistic (Mean=0)	1.453	Signif Level	0.154
Skewness	-0.198	Signif Level (Sk=0)	0.618
Kurtosis (excess)	0.773	Signif Level (Ku=0)	0.355
Jarque-Bera	1.288	Signif Level (JB=0)	0.525

Statistics on Series	Tanzania		
Annual Data From 1970:01 To 2010:01			
Observations	41		
Sample Mean	1.927	Variance	16.092
Standard Error	4.012	of Sample Mean	0.626
t-Statistic (Mean=0)	3.076	Signif Level	0.004
Skewness	-0.568	Signif Level (Sk=0)	0.153
Kurtosis (excess)	0.947	Signif Level (Ku=0)	0.257
Jarque-Bera	3.739	Signif Level (JB=0)	0.154

Statistics on Series	Thailand		
Annual Data From 1970:01 To 2010:01			
Observations	41		
Sample Mean	4.369	Variance	18.115
Standard Error	4.256	of Sample Mean	0.665
t-Statistic (Mean=0)	6.573	Signif Level	0.000
Skewness	-1.345	Signif Level (Sk=0)	0.001
Kurtosis (excess)	4.219	Signif Level (Ku=0)	0.000
Jarque-Bera	42.758	Signif Level (JB=0)	0.000

Statistics on Series	Trinidad & Tobago		
Annual Data From 1970:01 To 2010:01			
Observations	41		
Sample Mean	2.941	Variance	75.861
Standard Error	8.710	of Sample Mean	1.360
t-Statistic (Mean=0)	2.162	Signif Level	0.037
Skewness	1.057	Signif Level (Sk=0)	0.008
Kurtosis (excess)	2.444	Signif Level (Ku=0)	0.003
Jarque-Bera	17.841	Signif Level (JB=0)	0.000

Statistics on Series	Tunisia		
Annual Data From 1970:01 To 2010:01			
Observations	41		
Sample Mean	2.475	Variance	19.905
Standard Error	4.462	of Sample Mean	0.697
t-Statistic (Mean=0)	3.552	Signif Level	0.001
Skewness	0.945	Signif Level (Sk=0)	0.017
Kurtosis (excess)	4.533	Signif Level (Ku=0)	0.000
Jarque-Bera	41.197	Signif Level (JB=0)	0.000

Table B1 Continue

Statistics on Series	Hungary		
Annual Data From 197 0:01 To 2010:01			
Observations	40	Skipped/Missing	1
Sample Mean	1.961	Variance	11.184
Standard Error	3.344	of Sample Mean	0.529
t-Statistic (Mean=0)	3.709	Signif Level	0.001
Skewness	-1.331	Signif Level (Sk=0)	0.001
Kurtosis (excess)	3.052	Signif Level (Ku=0)	0.000
Jarque-Bera	27.331	Signif Level (JB=0)	0.000

Statistics on Series	Iceland		
Annual Data From 197 0:01 To 2010:01			
Observations	41		
Sample Mean	1.874	Variance	35.894
Standard Error	5.991	of Sample Mean	0.936
t-Statistic (Mean=0)	2.003	Signif Level	0.052
Skewness	0.308	Signif Level (Sk=0)	0.438
Kurtosis (excess)	1.667	Signif Level (Ku=0)	0.046
Jarque-Bera	5.395	Signif Level (JB=0)	0.067

Statistics on Series	Korea Rep		
Annual Data From 197 0:01 To 2010:01			
Observations	41		
Sample Mean	5.858	Variance	20.042
Standard Error	4.477	of Sample Mean	0.699
t-Statistic (Mean=0)	8.378	Signif Level	0.000
Skewness	-1.674	Signif Level (Sk=0)	0.000
Kurtosis (excess)	4.153	Signif Level (Ku=0)	0.000
Jarque-Bera	48.611	Signif Level (JB=0)	0.000

Statistics on Series	Lebanon		
Annual Data From 197 0:01 To 2010:01			
Observations	40	Skipped/Missing	1
Sample Mean	3.341	Variance	561.261
Standard Error	23.691	of Sample Mean	3.746
t-Statistic (Mean=0)	0.892	Signif Level	0.378
Skewness	0.127	Signif Level (Sk=0)	0.753
Kurtosis (excess)	2.279	Signif Level (Ku=0)	0.007
Jarque-Bera	8.761	Signif Level (JB=0)	0.013

Statistics on Series	Luxembourg		
Annual Data From 197 0:01 To 2010:01			
Observations	41		
Sample Mean	3.030	Variance	14.392
Standard Error	3.794	of Sample Mean	0.592
t-Statistic (Mean=0)	5.115	Signif Level	0.000
Skewness	-0.892	Signif Level (Sk=0)	0.025
Kurtosis (excess)	2.160	Signif Level (Ku=0)	0.010
Jarque-Bera	13.406	Signif Level (JB=0)	0.001

Statistics on Series	Macao		
Annual Data From 197 0:01 To 2010:01			
Observations	40	Skipped/Missing	1
Sample Mean	5.681	Variance	38.795
Standard Error	6.229	of Sample Mean	0.985
t-Statistic (Mean=0)	5.768	Signif Level	0.000
Skewness	1.201	Signif Level (Sk=0)	0.003
Kurtosis (excess)	3.092	Signif Level (Ku=0)	0.000
Jarque-Bera	25.562	Signif Level (JB=0)	0.000

Statistics on Series	Turkey		
Annual Data From 197 0:01 To 2010:01			
Observations	41		
Sample Mean	2.314	Variance	17.921
Standard Error	4.233	of Sample Mean	0.661
t-Statistic (Mean=0)	3.500	Signif Level	0.001
Skewness	-0.582	Signif Level (Sk=0)	0.143
Kurtosis (excess)	-0.301	Signif Level (Ku=0)	0.718
Jarque-Bera	2.471	Signif Level (JB=0)	0.291

Statistics on Series	United Kingdom		
Annual Data From 197 0:01 To 2010:01			
Observations	41		
Sample Mean	2.326	Variance	6.169
Standard Error	2.484	of Sample Mean	0.388
t-Statistic (Mean=0)	5.995	Signif Level	0.000
Skewness	-0.765	Signif Level (Sk=0)	0.054
Kurtosis (excess)	1.348	Signif Level (Ku=0)	0.106
Jarque-Bera	7.104	Signif Level (JB=0)	0.029

Statistics on Series	United Sattes		
Annual Data From 197 0:01 To 2010:01			
Observations	41		
Sample Mean	1.726	Variance	5.860
Standard Error	2.421	of Sample Mean	0.378
t-Statistic (Mean=0)	4.567	Signif Level	0.000
Skewness	-0.809	Signif Level (Sk=0)	0.042
Kurtosis (excess)	0.774	Signif Level (Ku=0)	0.354
Jarque-Bera	5.500	Signif Level (JB=0)	0.064

Statistics on Series	Uruguay		
Annual Data From 197 0:01 To 2010:01			
Observations	41		
Sample Mean	2.308	Variance	31.960
Standard Error	5.653	of Sample Mean	0.883
t-Statistic (Mean=0)	2.614	Signif Level	0.013
Skewness	-0.689	Signif Level (Sk=0)	0.083
Kurtosis (excess)	0.410	Signif Level (Ku=0)	0.623
Jarque-Bera	3.529	Signif Level (JB=0)	0.171

Statistics on Series	Venezuela		
Annual Data From 197 0:01 To 2010:01			
Observations	41		
Sample Mean	0.278	Variance	37.859
Standard Error	6.153	of Sample Mean	0.961
t-Statistic (Mean=0)	0.289	Signif Level	0.774
Skewness	0.011	Signif Level (Sk=0)	0.978
Kurtosis (excess)	-0.238	Signif Level (Ku=0)	0.776
Jarque-Bera	0.097	Signif Level (JB=0)	0.953

Statistics on Series	Vietnam		
Annual Data From 197 0:01 To 2010:01			
Observations	40	Skipped/Missing	1
Sample Mean	4.172	Variance	11.862
Standard Error	3.444	of Sample Mean	0.545
t-Statistic (Mean=0)	7.661	Signif Level	0.000
Skewness	-0.642	Signif Level (Sk=0)	0.111
Kurtosis (excess)	0.642	Signif Level (Ku=0)	0.448
Jarque-Bera	3.437	Signif Level (JB=0)	0.179

Table B1 Continue

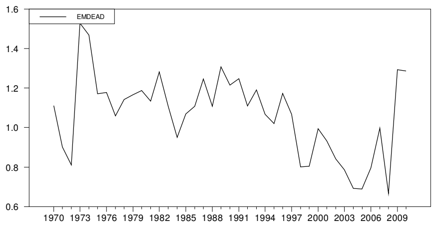
Statistics on Series	Madagascar		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	-1.035	Variance	15.681
Standard Error	3.960	of Sample Mean	0.618
t-Statistic (Mean=0)	-1.673	Signif Level	0.102
Skewness	-1.560	Signif Level (Sk=0)	0.000
Kurtosis (excess)	5.109	Signif Level (Ku=0)	0.000
Jarque-Bera	61.215	Signif Level (JB=0)	0.000

Statistics on Series	Zambia		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	-0.012	Variance	71.958
Standard Error	8.483	of Sample Mean	1.325
t-Statistic (Mean=0)	-0.009	Signif Level	0.993
Skewness	1.561	Signif Level (Sk=0)	0.000
Kurtosis (excess)	4.819	Signif Level (Ku=0)	0.000
Jarque-Bera	56.337	Signif Level (JB=0)	0.000

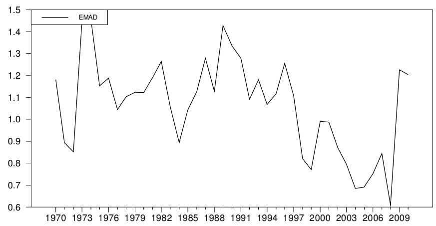
Statistics on Series	Malawi		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	1.098	Variance	55.239
Standard Error	7.432	of Sample Mean	1.161
t-Statistic (Mean=0)	0.946	Signif Level	0.350
Skewness	-0.559	Signif Level (Sk=0)	0.159
Kurtosis (excess)	0.332	Signif Level (Ku=0)	0.691
Jarque-Bera	2.325	Signif Level (JB=0)	0.313

Statistics on Series	Zimbabwe		
Annual Data From 197	0:01 To 2010:01		
Observations	41		
Sample Mean	0.496	Variance	67.496
Standard Error	8.216	of Sample Mean	1.283
t-Statistic (Mean=0)	0.386	Signif Level	0.701
Skewness	-0.150	Signif Level (Sk=0)	0.707
Kurtosis (excess)	-0.318	Signif Level (Ku=0)	0.704
Jarque-Bera	0.325	Signif Level (JB=0)	0.850

Appendix C. Euclidean distance computed on the economic "deviation cycles"

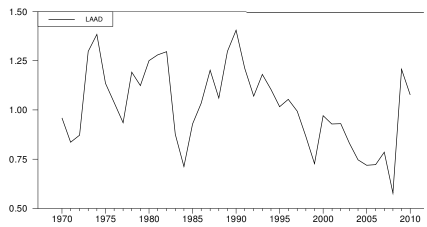


1 EEs plus DEs vs AEs

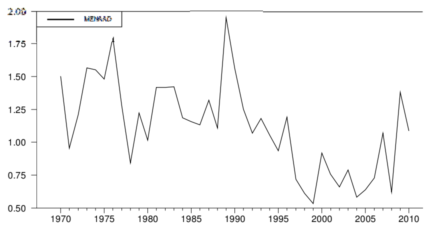


2 EEs vs AEs

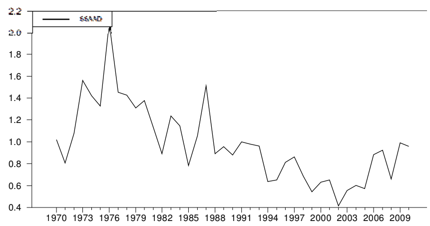
Fig. C.1 Euclidean distance computed on deviation cycles: EEs plus DEs vs. AEs and EEs vs. AEs



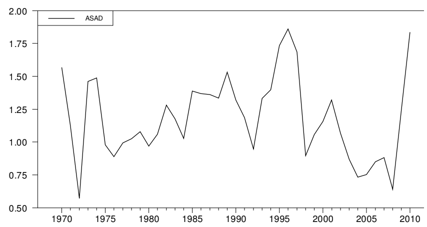
1.Latin America EEs vs AEs



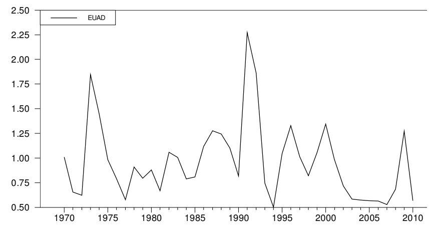
2. MENA EEs vs AEs



3. Sub Sahara Africa EEs vs AEs



4. Asia EEs vs AEs



5. Europe EEs vs AEs

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

Appendix D. Priors, posteriors distributions and the computational method

The prior distributions proposed in this chapter are chosen according to previous experiences from related literature and because of their intuitiveness and convenience in the applications.

Prior densities are assumed for $\xi_0 = (\Omega^{-1}, B, \theta_0)$, and σ^2 is assumed to be known. The elements of ξ_0 are assumed to be independent. They are the parameters of the probability density functions of the innovations υ_t and η_t and the initial state of the coefficients in system (3.6)-(3.7); hence, the assumption of independencies is very reasonable and, in fact, is a very common assumption in the related literature; therefore

$$P(\theta_0, \Omega, B) = P(\theta_0)P(\Omega)P(B) \qquad (d1)$$

The matrix Ω with dimension $(NG \times NG)$ is the variance/covariance matrix of the residuals E_t and so Ω^{-1} is the precision matrix. In Bayesian statistics, the Wishart distribution[73], namely a probability distribution of symmetric positive-definite random matrix, is often used as the prior for the precision matrix, and also 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:

$$\Omega^{-1} \sim W(z_1,\ Q_1) \qquad (d2)$$

The matrix B, whose dimension is $R \times R$ where $R = \sum_{f=1}^{F} dim_f$, is the variance/covariance matrix of the innovation η_t. To guarantee orthogonality of factors, the matrix B must be block-diagonal, hence, $B = diag(B_1, \dots, B_F)$. For $f = 1, \dots, F$ each block B_f, whose dimension is $dim_f \times dim_f$, 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[74] which is distributed like an inverse gamma with shape parameter $\left({}^{\rho}/_{2}\right)$ and scale parameter $\left({}^{\varrho}/_{2}\right)$:

$$b_f \sim IG\left({}^{\rho}/_{2},\ {}^{\varrho}/_{2}\right) \qquad (d3)$$

The law of motion for the factors (eq. 3.5) implies that for $t = 1, \dots, T$ $\theta_t | \theta_{t-1}, B \sim N(\theta_{t-1}, B)$, and so

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

[74] Let me note that the block diagonality of the matrix B is preserved also a posteriori, this means that factors are orthogonal also a posteriori and this guarantees their a posteriori identifiability.

$$P(\theta_1, \dots, \theta_T | \theta_0, B) = \prod_{t=1}^{T} P(\theta_t | \theta_{t-1}, B)$$

$$\propto |B|^{-\frac{T}{2}} exp\left\{-\frac{1}{2}\sum_{t=1}^{T}(\theta_t - \theta_{t-1})' B^{-1}(\theta_t - \theta_{t-1})\right\} \qquad (d4)$$

where the symbol "∝" stands for "proportional". The prior for θ_0 is assumed to be normal

$$\theta_0 \sim N(\bar{\theta}_0, \bar{R}_0) \qquad (d5)$$

The values of the vector of hyperparameters $\mu = \left(z_1, Q_1, \alpha, b, \bar{\theta}_0, \bar{R}_{0,}\sigma^2\right)$ are selected either to produce rather loose priors (this is the case for $z_1, Q_1, \alpha, b, \bar{R}_0$), or chosen observing the data (the case for $\bar{\theta}_0$), or chosen to maximize the model in-sample fit of data (the case for σ^2).

The hyperparameter z_1 is set equal to $NG + 50$, namely 162 (i.e., dimension of the squared matrix Ω plus 50) because, for the Wishart distribution to be proper, the degrees of freedom must be[75] at least equal to the dimension of the matrix Ω. In some related literature (e.g., Cogley and Sargent (2003), Cogley (2003), Primiceri (2005), or Canova et al. (2007)), the scale matrix Q_1 is chosen to be the inverse of variance/covariance matrix of the corresponding Ordinary Least Square estimates on a training sample. In this work, owing to available data, 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; however, also in this case the prior probability density function on Ω allows for posterior non diagonal matrix, namely allows for the case of posterior correlated residuals between equations. The hyperparameters ρ and ϱ are set at 1 and 5, respectively. Following the related literature (e.g. Canova and Ciccarelli (2009)) $\bar{\theta}_0$ is the Ordinary Least Squares estimate in the time-invariant version of the model, and the matrix $\bar{R}_0$ is assumed to be $\bar{R}_0 = I_R$ where I_R is identity matrix whose dimension is $R \times R$ (remind that $R = \sum_{f=1}^{F} dim_f$). Since the in-sample fit improves if σ^2 goes to zero, an exact factorization of δ_t is used.

To compute the posterior distribution for $\xi = (\Omega^{-1}, b_1, \dots, b_F, \{\theta_t\}_{t=1}^{T})$ the prior is combined with the likelihood $\mathcal{L}(\xi | Y_1, \dots, Y_T)$ which (conditional to the first p observations before Y_1) is proportional to:

[75] See Greenberg (2008) pag. 190.

$$\mathcal{L}(\xi|Y_1,\dots,Y_T) \propto |\Omega|^{-\frac{T}{2}} exp\left\{-\frac{1}{2}\sum_{t=1}^{T}(Y_t - W_t\Xi\theta_t)'\Omega^{-1}(Y_t - W_t\Xi\theta_t)\right\} \qquad (d6)$$

As explained in Greenberg (2008), using the Bayes rule[76], the likelihood of data $(d6)$ and the prior probability density functions $(d1)$-$(d5)$ the posterior distribution for ξ is proportional to:

$$P(\Omega^{-1}, b_1, \dots, b_F, \{\theta_t\}_{t=1}^{T}|Y_1,\dots,Y_T) \propto |\Omega|^{-\frac{T}{2}} exp\left\{-\frac{1}{2}\sum_{t=1}^{T}(Y_t - W_t\Xi\theta_t)'\Omega^{-1}(Y_t - W_t\Xi\theta_t)\right\}$$
$$\times |\Omega|^{-\frac{(z_1-NG-1)}{2}} exp\left\{-\frac{1}{2}tr(Q_1\Omega^{-1})\right\}$$
$$\times \prod_{i=1}^{F} b_i^{-\left(\frac{\varrho}{2}+1\right)} exp\left\{-\frac{\varrho}{2b_i}\right\} \qquad (d7)$$
$$\times |B|^{-\frac{T}{2}} exp\left\{-\frac{1}{2}\sum_{t=1}^{T}(\theta_t - \theta_{t-1})'B^{-1}(\theta_t - \theta_{t-1})\right\}$$

and to compute the conditional posterior distribution of each parameter we can consider only the terms in the joint posterior $(d7)$ that contain the parameter of interest. Let be $\xi_{-\mathcal{K}}$ the vector ξ excluding the parameter $\mathcal{K}$. After few algebraic passages (see Koop, 2010) it is obtained:

$$\Omega^{-1}|Y_1,\dots,Y_T,\xi_{-\Omega} \sim W\left(z_1 + T, \left(Q_1^{-1} + \textstyle\sum_t (Y_t - W_t\Xi\theta_t)\,(Y_t - W_t\Xi\theta_t)'\right)^{-1}\right) \quad (d8)$$

$$b_f|Y_1,\dots,Y_T,\xi_{-b_f} \sim IG\left(\frac{\varrho + T*dim_f}{2}, \frac{\varrho + \sum_t(\theta_{ft}-\theta_{ft-1})'(\theta_{ft}-\theta_{ft-1})}{2}\right),\; f = 1,\dots,F \quad (d9)$$

The $(d8)$ and $(d9)$ have been used in the Gibbs sampling algorithm[77] to draw samples of the parameters Ω^{-1}, b_f for $f = 1,\dots,F$; but to complete the algorithm it is needed a means of drawing from $P(\theta_t|Y_1,\dots Y_T,\xi_{-\theta_t})$. Canova et al. (2007) (see also Canova 2007, page 378) show that

$$\theta_t|Y_1,\dots,Y_T,\xi_{-\theta_t} \sim N(\bar{\theta}_{t|T}, \bar{V}_{t|T}),\;\; t \le T \qquad (d10)$$

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).

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[76] From the Bayes rule (see for example Koop 2003, among others) $P(\xi|Y_1,\dots,Y_T) = \frac{P(\xi)\mathcal{L}(\xi|Y_1,\dots,Y_T)}{P(Y_1,\dots,Y_T)} \propto \mathcal{L}(\xi|Y_1,\dots,Y_T)P(\xi)$.

[77] The Gibbs sampling is an algorithm which draws sequentially the samples of parameters from the conditional posterior distributions (see Greenberg 2008 or Gelfand 2000 for more details on the Gibbs sampling).

The posterior density functions $(d8) - (d10)$ have been used for sampling in the Gibbs sampling algorithm, as follows:

1. Initiate the algorithm by choosing $b_f^0 = 0.01$ for $f = 1, \dots F$
2. At the first iteration, draw

   $\theta^{(1)} = (\theta_1^1, \theta_2^1, \dots, \theta_T^1)$ with the Kalman smoother as in Chib Greenberg (1995) knowing b_f^0 for $f = 1, \dots F$

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

   ${b_f}^{(1)}$ from the conditional posterior distribution $P\left(b_f | Y_1, \dots, Y_T, \theta^{(1)}\right)$, $f = 1, \dots, F$
3. At the g^{th} iteration, draw

   $\theta^{(g)} = \left(\theta_1^g, \theta_2^g, \dots, \theta_T^g\right)$ with the Kalman smoother as in Chib Greenberg (1995) knowing b_f^{g-1} for $f = 1, \dots F$

   $\Omega^{(g)}$ from the conditional posterior distribution $P\left(\Omega | Y_1, \dots, Y_T, \theta^{(g)}\right)$

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

until the desired number of iterations is obtained. Once the posterior distribution of θ_t is available it can be constructed the posterior distribution of the indicators; for example, the posterior mean of the indicator GI_t can be approximated by $(1/\mathcal{G}) \sum_{g=}^{\mathcal{G}} \mathcal{W}_{1t} \theta_{1t}^g$, where $\mathcal{G}$ is the number of draws, 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 has been checked by increasing the length of the chain. The results presented in this chapter 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.

Appendix E. Historical decomposition of GDP fluctuations

The figure E.1 plots the historical fluctuations of GDP, the global component, the regional component and the idiosyncratic component (namely the country specific component and the residual term).

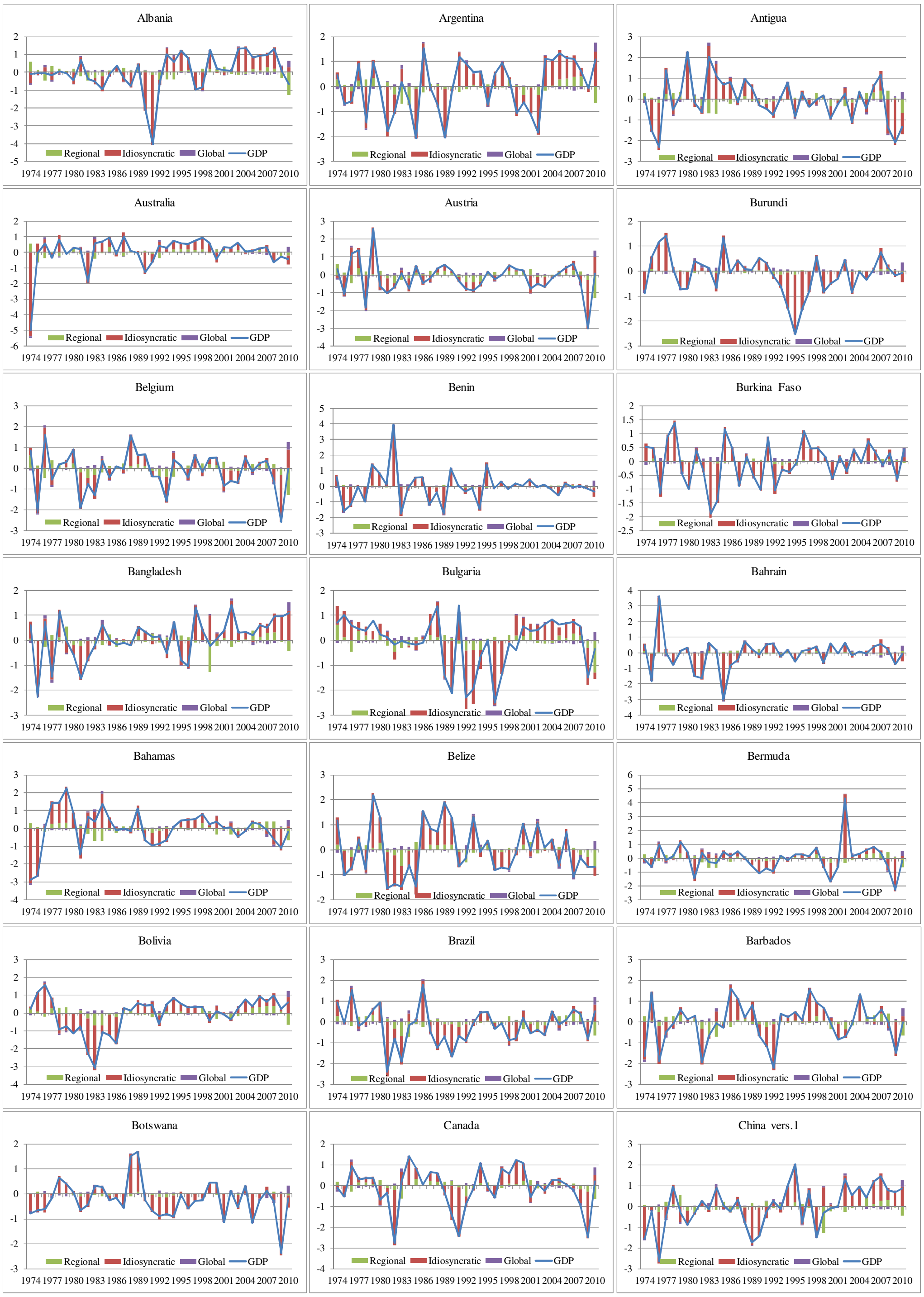

Fig. E.1 Historical decomposition of GDP fluctuations

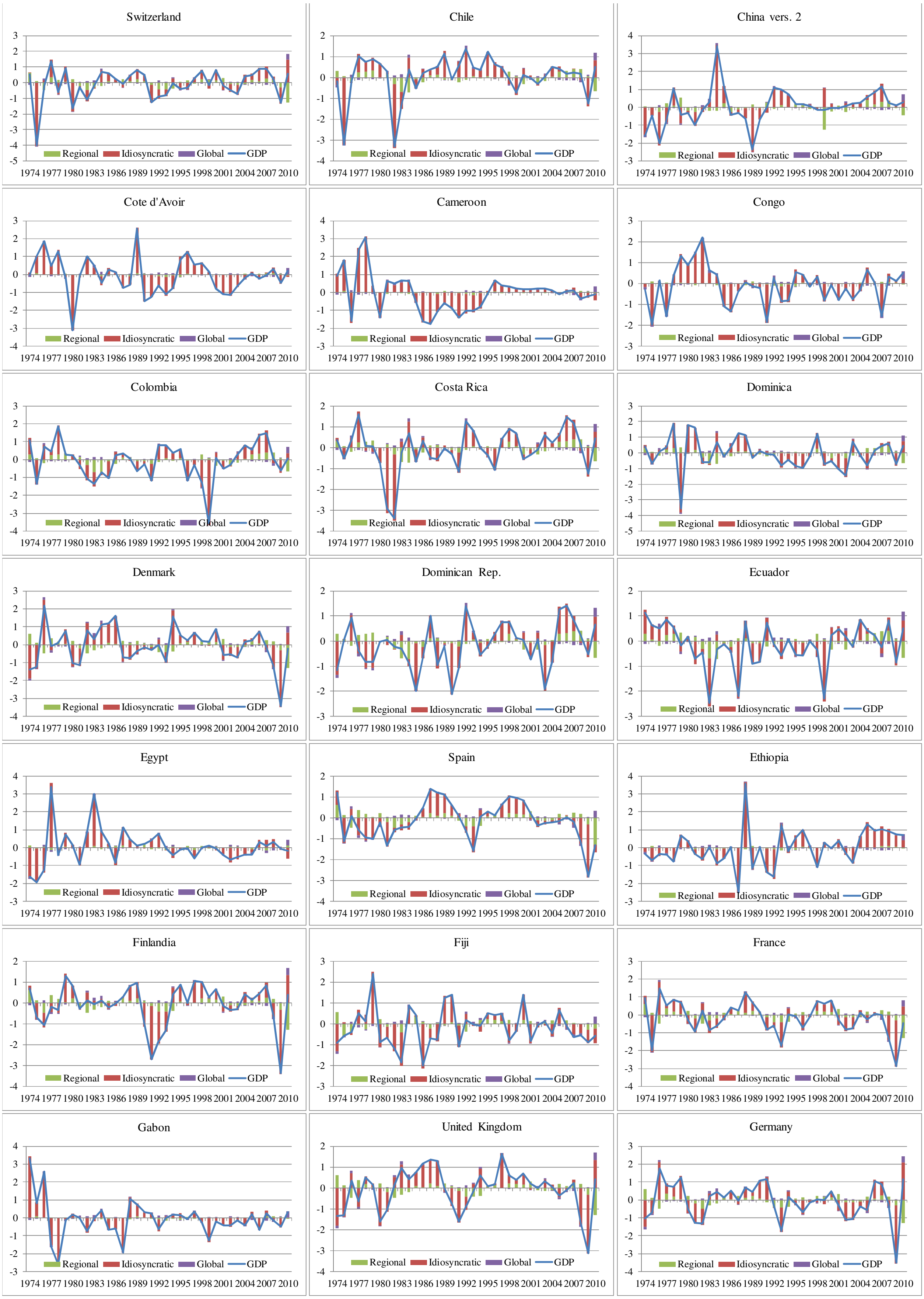

Fig. E.1 Continue

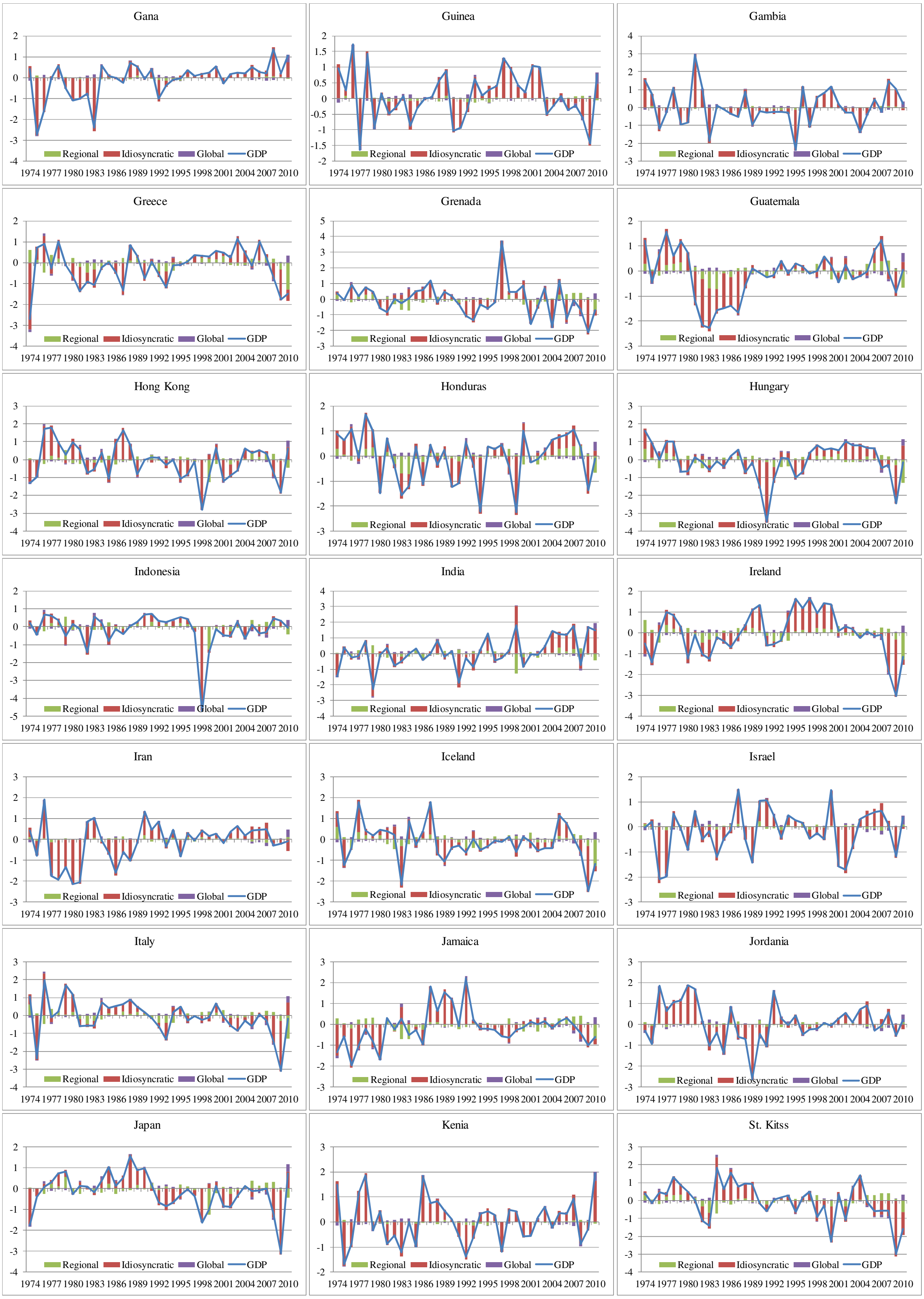

Fig. E.1 Continue

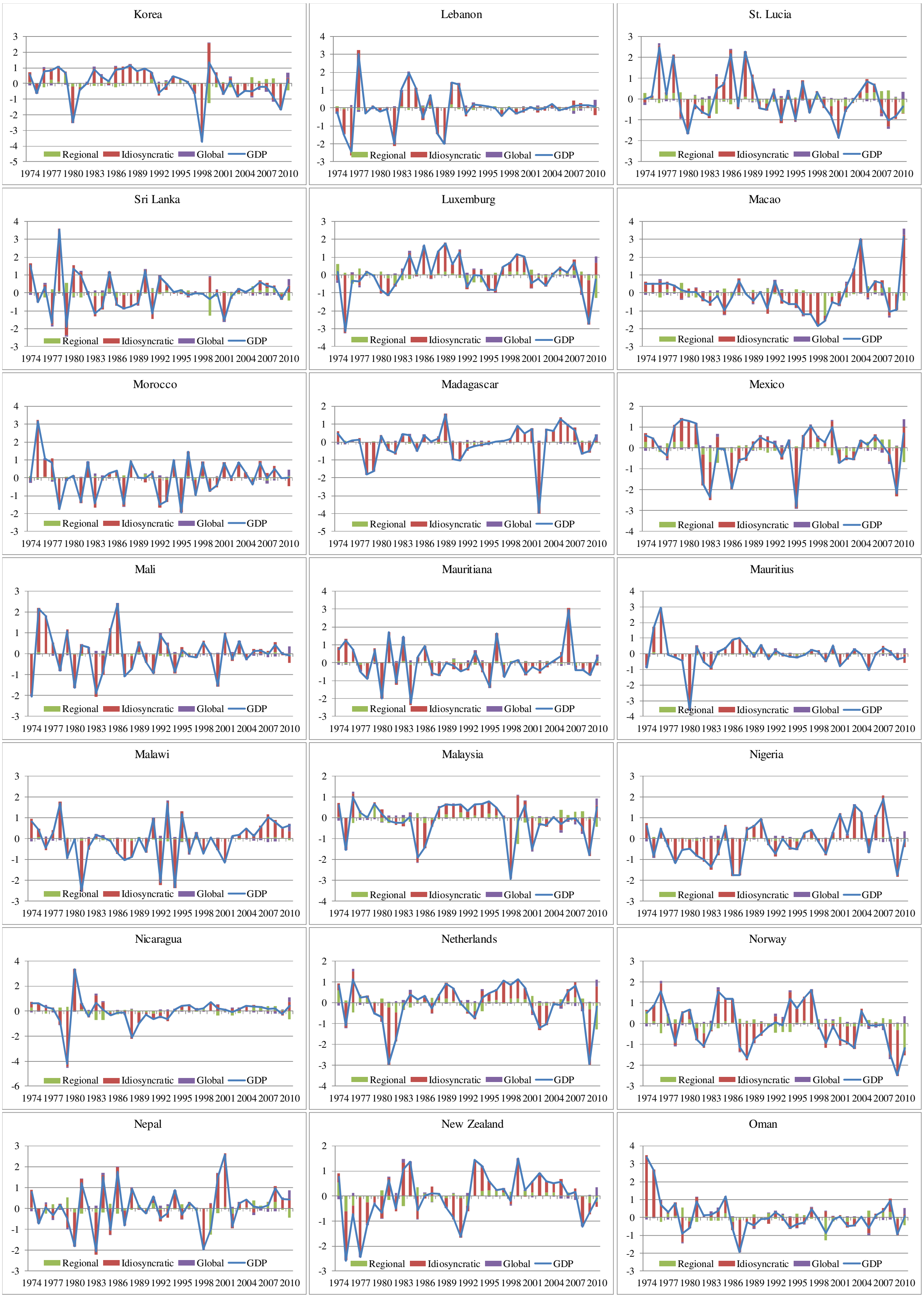

Fig. E.1 Continue

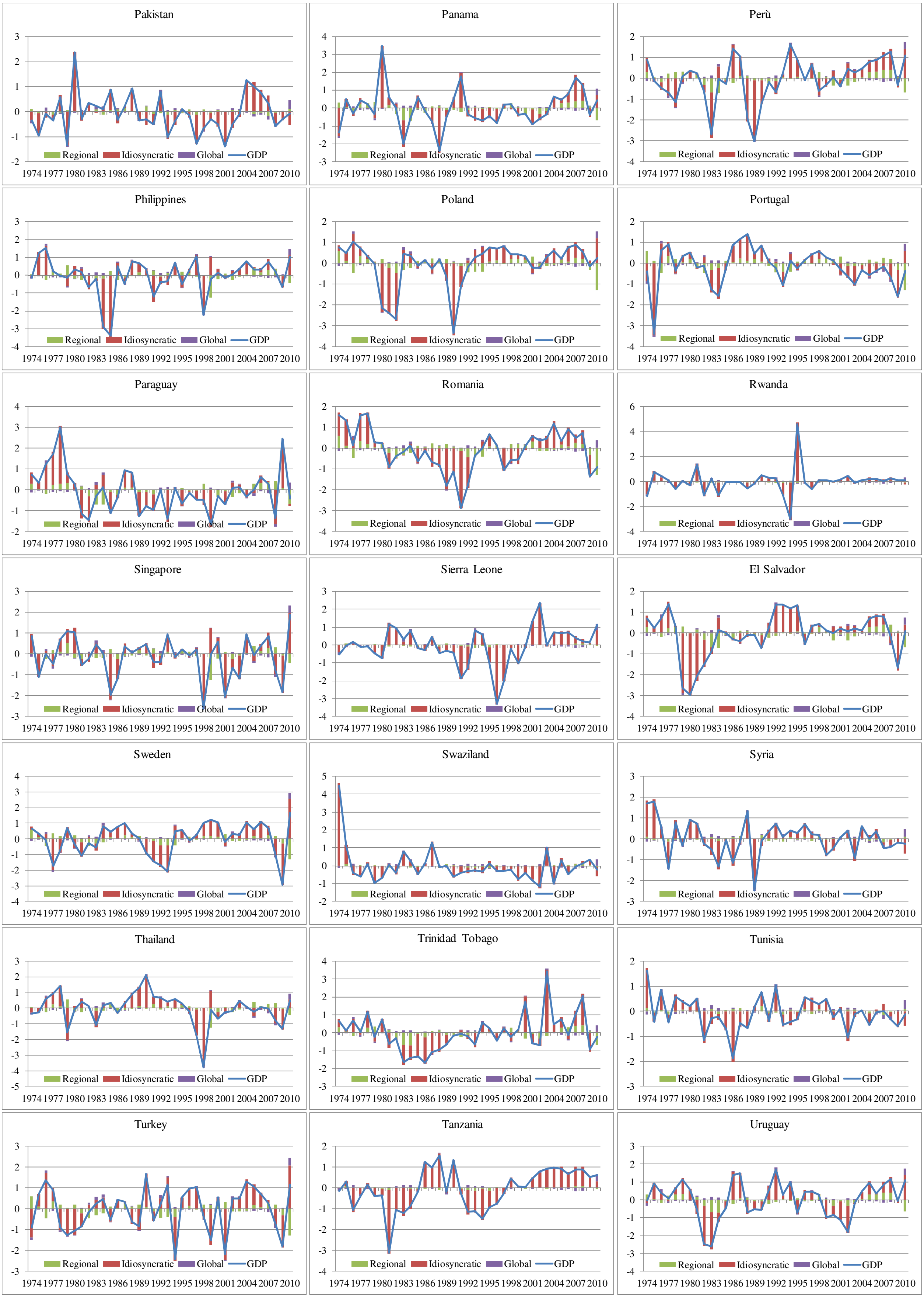

Fig. E.1 Continue

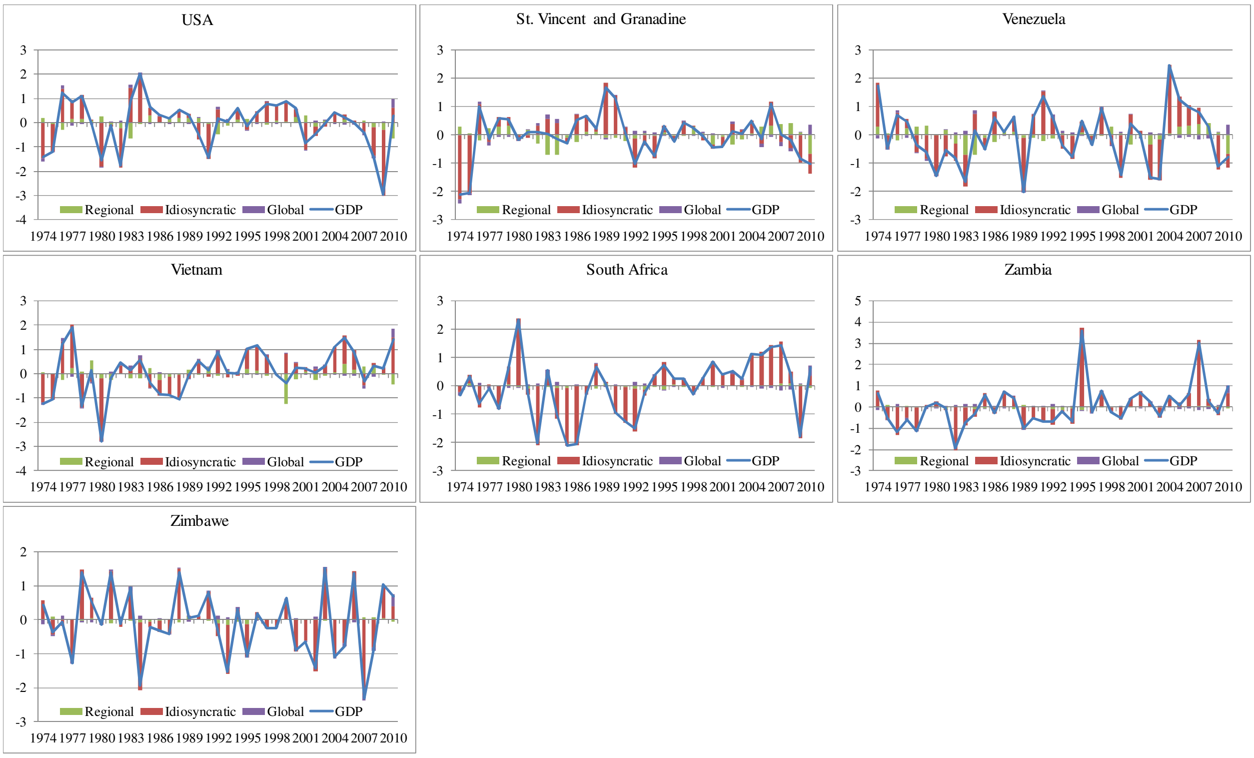

Fig. E.1 Continue

Appendix F. Additional results

This appendix proposes additional results obtained with counter factual experiments which, differently from those one presented in sub-section 2.3.5.2, have been performed on the model estimated on the entire data sample (1970-2010). Using the full set of data, instead of on the data until the time of the simulated shock, allows to consider a richer set of information in the estimation procedure.

The main advantage of using the model estimated on the full set of information is that the CAs can be performed also for the first years of the sample period because also the parameters estimated at the beginning of the sample period are based on a rich set of information; and so I believe that also this exercise, which is in some way in the same logic of the ex-post forecast econometric exercises often presented in the empirical literature, could confirm and make robust the results discussed in subsection 2.3.5.2 of chapter 2.

Both the immediate impact and the cumulated impact have been computed on the sample period from 1981-2010.

Table F.1 presents the median responses of EEs together with the lower and upper values of the credible intervals (16th and 84th percentiles, respectively) for different sub-samples.

The resilience of EEs (see also Figure F.1) was higher during the last fifteen years of the sample period than in the preceding fifteen, both when the evaluation is made in terms of the immediate impact and when it is made in terms of the cumulated impact. During the period 1996-2010, for example, the cumulated impact was about 15% lower

Table F.1 Dynamic impact of the adverse scenario in AEs on EEs; additional results

	t+1			*t+2*			*t+3*			*t+4*			Cumulated median impact		
	U	M	L	U	M	L	U	M	L	U	M	L	U	M	L
1981-1995	-0.037	-0.134	-0.235	-0.005	-0.050	-0.098	-0.035	-0.074	-0.117	-0.066	-0.136	-0.212	-0.143	-0.394	-0.663
1996-2010	-0.036	-0.127	-0.222	-0.007	-0.044	-0.088	-0.001	-0.039	-0.082	-0.065	-0.122	-0.187	-0.108	-0.333	-0.580
Subsamples															
1981-1985	-0.047	-0.154	-0.262	0.003	-0.046	-0.099	-0.048	-0.091	-0.138	-0.062	-0.140	-0.226	-0.153	-0.431	-0.725
1986-1990	-0.010	-0.096	-0.184	-0.022	-0.060	-0.103	-0.016	-0.056	-0.099	-0.068	-0.129	-0.193	-0.117	-0.341	-0.579
1991-1995	-0.067	-0.168	-0.276	0.010	-0.037	-0.088	-0.037	-0.072	-0.110	-0.068	-0.137	-0.217	-0.162	-0.413	-0.690
1996-2000	-0.018	-0.105	-0.193	-0.011	-0.046	-0.088	0.006	-0.030	-0.071	-0.065	-0.123	-0.186	-0.088	-0.304	-0.539
2001-2005	-0.054	-0.151	-0.253	0.000	-0.040	-0.085	-0.004	-0.044	-0.091	-0.061	-0.119	-0.182	-0.118	-0.353	-0.612
2006-2010	-0.036	-0.170	-0.281	-0.007	-0.037	-0.088	-0.001	-0.055	-0.105	-0.065	-0.131	-0.209	-0.108	-0.393	-0.683

Note: M stands for median, L and U stand for lower and upper values of the credible interval, respectively (16th and the 84th percentiles).

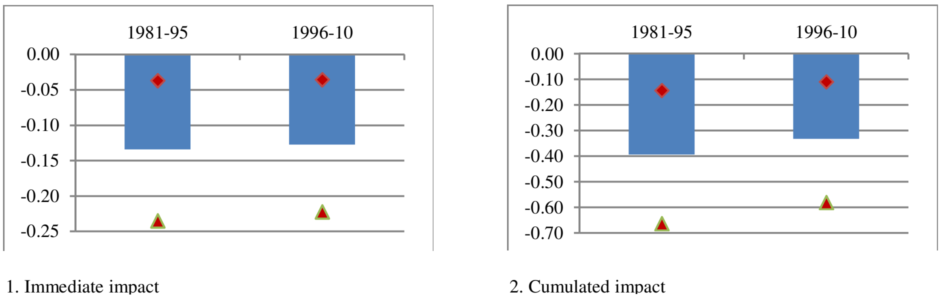

Fig. F.1 Impact (median, 16th - 84th percentiles) on EEs of shocks spreading from the AEs; additional results

than in the period 1981-1995.

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 1981-1995 period.

Let us break down the whole sample period in smaller sub-samples (five-years). If we observe the last fifteen years of the sample period, we see that the resilience of the EEs fell rather than rose. The immediate impact (also shown in Figure F.2, 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 was 40% higher than that measured during the previous five-year period 1996-2000. The same conclusions are reached if the results obtained for the cumulated impacts are considered (Figure F.2, panel 2). Nevertheless if we extend the timeframe we see that, despite the increase in the intensity of impacts during the last fifteen years (1996-2010), the cumulated 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 2000s is greater than it was during the early 1980s.

The above results broadly confirm the conclusion exposed in the sub-section 2.3.5.2 in this chapter.

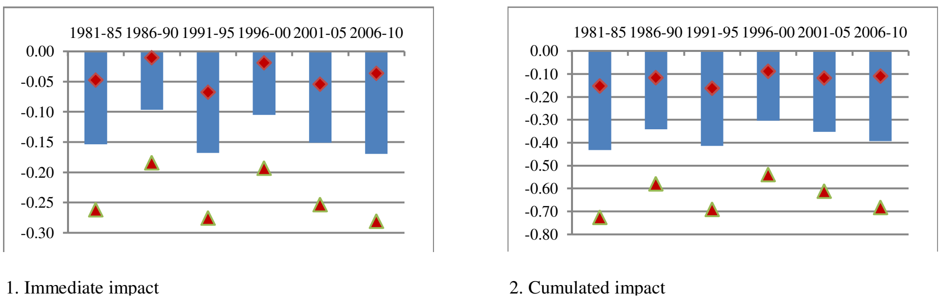

Fig. F.2 Impact (median, 16th - 84th percentiles) on EEs of shocks spreading from the AEs; additional results

4. International (spillovers in) macroeconomic-credit linkages and the decoupling phenomenon

1. Introduction

This chapter extends the empirical investigation of chapter 3 by considering also the bank landing variable. Financial liberalization increased sharply in the globalization period; many structural changes took place among emerging economies and improved the degree of liberalization of financial systems. For example the liberalization of domestic banking systems and stock markets, and the removal of some restrictions on the acquisition of assets by foreigners (see Lane and Milesi Ferretti, 2007).

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 on a set of 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 of countries, and in the spread of shocks across countries, see for example Cetorelli and Goldberg (2008, 2010).

As in the chapter 3, in this one the empirical investigation was performed by using a Time Varying PANEL VAR econometric model, and following two steps. The first involved the implementation of three different model specifications in terms of their coefficients factorization.

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 analysis (CA) experiments and to evaluate the reaction of the GDP of EEs' to financial shocks (in terms of credit shocks) coming from the AEs, in addition to the real shocks (in terms of GDP shocks) spreading from such countries.

This chapter is of course closely related to the literature on decoupling but it is also related to the most recent studies on the international transmission of real and credit shocks e.g. Galesi and Sgherri (2009), Helbling, Huidrom, Kose, and Otrok (2011) or Devereux and Yetman (2010). Indeed that literature 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. With this chapter I aims also to fill this gap and analyse the force with which shocks in the AEs spreads to the EEs; moreover it aims to identify those external shocks, either real or credit, to which the EEs are most vulnerable.

One of the main conclusions of the empirical investigation performed in this chapter 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 credit or a real nature. The results presented in this chapter are in line with those presented in the chapter 3. More specifically, the last five years of the period on question (i.e., 1996-2010) have witnessed the greatest resilience of the EEs. Over the course of the years, there has been a change in the relationship between the AEs and the EEs which lends support to the decoupling hypothesis; nevertheless, it need to 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 others of lesser resilience, and vice-versa. Another interesting result is that during almost the entire period analysed here, the EEs have been more vulnerable to external shocks of a credit kind than to those of a real kind; moreover, this 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 chapter is organized as follows. The next section presents the dataset used in this chapter, shortly recalls the methodology adopted, and discusses the results of the CA experiments; section 3 presents the conclusions of this chapter.

2. Empirical analysis

2.1 Countries and dataset

The appendix G shows the list of the 78 countries used as sample, of which 17 European countries, 3 Central and North American countries, 21 Latin American countries, 13 Asian countries, 9 MENA countries, 12 SSA countries and 3 Oceania countries. The database contains 43 EEs, 14 DEs and 21 AEs countries. The countries cover about 86% of the world's GDP (at PPP) and more than 79% of the world's population[78]. As in the previous chapter, all countries of the sample have a rating at least

[78] Own computation on data provided by the IMF, WEO Database, April 2013.

"C" in the Penn World Table ranking, and have been grouped in AEs, EEs and Des groups according to Pritchett (2000)[79]. In this chapter, I used annual data on the growth rate of the GDP and the growth rate of the credit from 1978 to 2010 years. In particular, I used the annual growth rate of the real gross domestic product per head at purchasing power parity collected by the Penn World Table 7.1[80] database, and the annual growth rate of the domestic credit provided by the banking sector[81] collected by the World Development Indicators (WDI) of the World Bank. The growth rate of credit has been deflated by using the GDP deflator collected by the WDI database.

In this chapter the dataset is slightly different with respect to the dataset used in the previous chapter because here I have adapted the dataset to consider also the credit variable, in the sense that the availability of data on the credit variable has conditioned

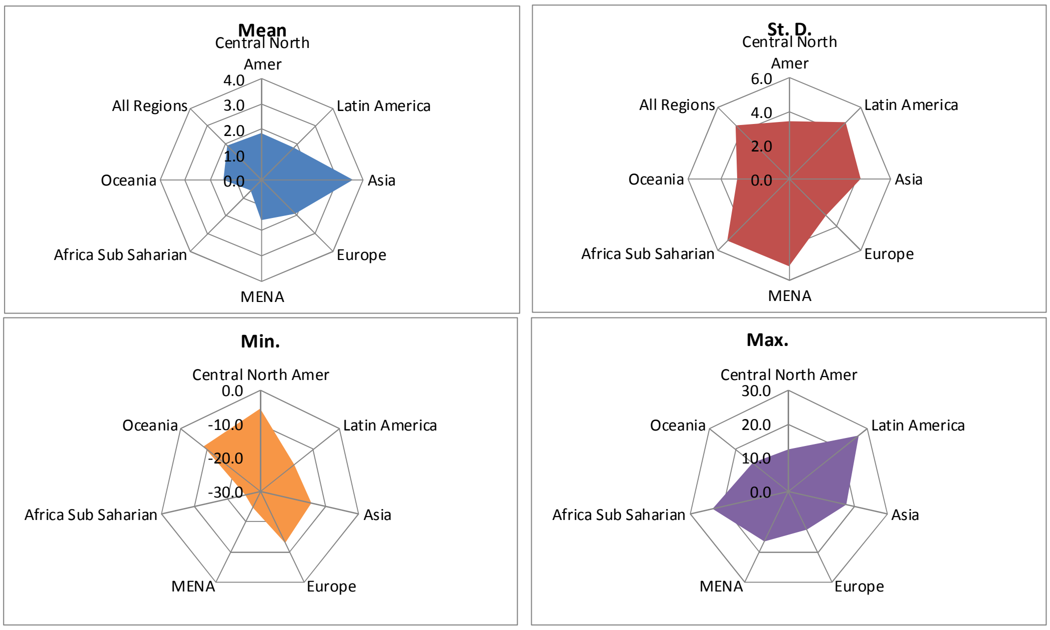

Fig. 4.1 Main stylized facts of GDP growth rate (%) along the regional dimension

[79] As it has already said in chapter 3, the 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. However, 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.

[80] 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.

[81] As explained in the catalog of the WDI, the domestic credit provided by the banking sector includes all credit to various sectors. The banking sector includes monetary authorities and deposit money banks, as well as other banking institutions where data are available.

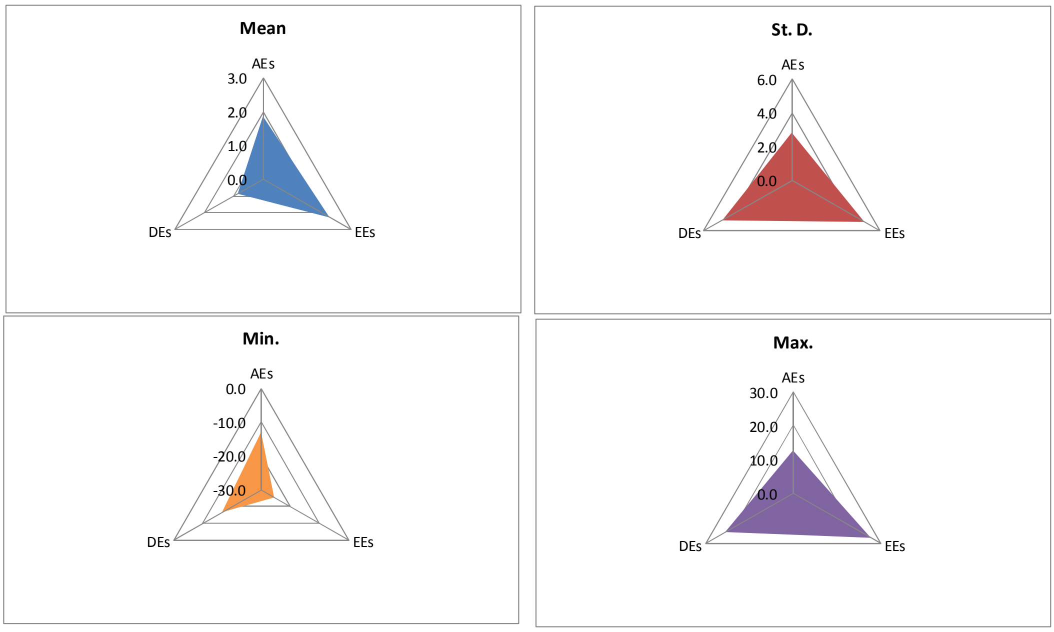

Fig. 4.2 Main stylized facts of GDP growth rate (%) along the economic type dimension

the construction of the dataset.

Even if the set of countries and the length of the time series is not exactly the same of the chapter 3, some of the main descriptive statistics of the GDP dataset in this chapter are very similar to the equivalent descriptive statistics of the GDP dataset in the previous chapter. In the entire dataset the average GDP growth rate (in per cent point) is 1.9 with a standard deviation at 4.5, the minimum at -25.5 and the maximum at 26.6 (see Figure 4.1).

If we explore the dataset along the regional dimension (Central North America, Latin America, Asia, Europe, MENA, ASS, Oceania) we can see the Asian region to have the highest average GDP growth rate, about twice as much as the average of the entire dataset (see Figure 4.1); moreover, as highlighted in the Figure, the ASS and the MENA regions have the highest standard deviations, and the highest contraction of the GDP growth rate is recorded within the MENA region, while the record high is recorded within the Latin America area.

Along the economic type dimension (see Figure 4.2), we have that the average GDP growth rate in EEs is the highest, and the standard deviations are quite similar in in the EEs and DEs groups and they are higher than AEs group's standard deviation.

From Table 4.1 it is possible to see the main stylized facts for the GDP fluctuations in sub-group of countries "crossing" the regional and the economic type

Table 4.1 Main stylized facts of GDP in sub-groups of countries

	Central North America				Latin America				Asia				Europe			
	Mean	St. D.	Min.	Max.	Mean	St. D.	Min.	Max.	Mean	St. D.	Min.	Max.	Mean	St. D.	Min.	Max.
AEs	1.6	2.3	-5.5	6.6	n.a.	n.a.	n.a.	n.a.	1.9	2.7	-7.1	7.0	1.9	3.0	-13.0	12.6
EEs	n.a.	n.a.	n.a.	n.a.	1.9	4.8	-17.1	26.6	4.1	4.5	-14.4	17.6	2.0	4.4	-7.9	9.3
DEs	2.2	4.9	-5.2	12.5	0.6	3.6	-7.1	7.2	2.2	3.0	-5.1	10.4	n.a.	n.a.	n.a.	n.a.
All Types	1.8	3.4	-5.5	12.5	1.8	4.7	-17.1	26.6	3.6	4.3	-14.4	17.6	1.9	3.1	-13.0	12.6

	MENA				Africa Sub Saharian				Oceania				All Regions			
	Mean	St. D.	Min.	Max.	Mean	St. D.	Min.	Max.	Mean	St. D.	Min.	Max.	Mean	St. D.	Min.	Max.
AEs	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	1.8	1.7	-2.8	4.7	1.9	2.8	-13.0	12.6
EEs	1.6	5.2	-24.8	16.5	1.0	5.5	-25.5	11.9	n.a.	n.a.	n.a.	n.a.	2.3	4.9	-25.5	26.6
DEs	n.a.	n.a.	n.a.	n.a.	0.4	5.1	-16.7	23.2	0.9	4.8	-8.6	13.5	0.9	4.8	-16.7	23.2
All Types	1.6	5.2	-24.8	16.5	0.6	5.2	-25.5	23.2	1.5	3.1	-8.6	13.5	1.9	4.5	-25.5	26.6

dimensions[82]. Among the EEs, the Asian emerging countries have the highest average rate of GDP growth instead in the ASS emerging countries there is the highest standard deviation. Among the AEs, the Asian and European advanced economy countries have the highest average growth rate while the standard deviation in the European advanced economy is the highest.

The credit dataset has high heterogeneity. When the entire dataset is considered, the average growth rate (%) of the credit variable is -8.7; the Latin America is the region with the worst average dynamic of the credit variable while the best one is in the Central North America region, see Figure 4.3. As highlighted in the Figure, along the regional dimension the Latin America is the region with the higher standard deviation, and the Central North America has the lower standard deviation.

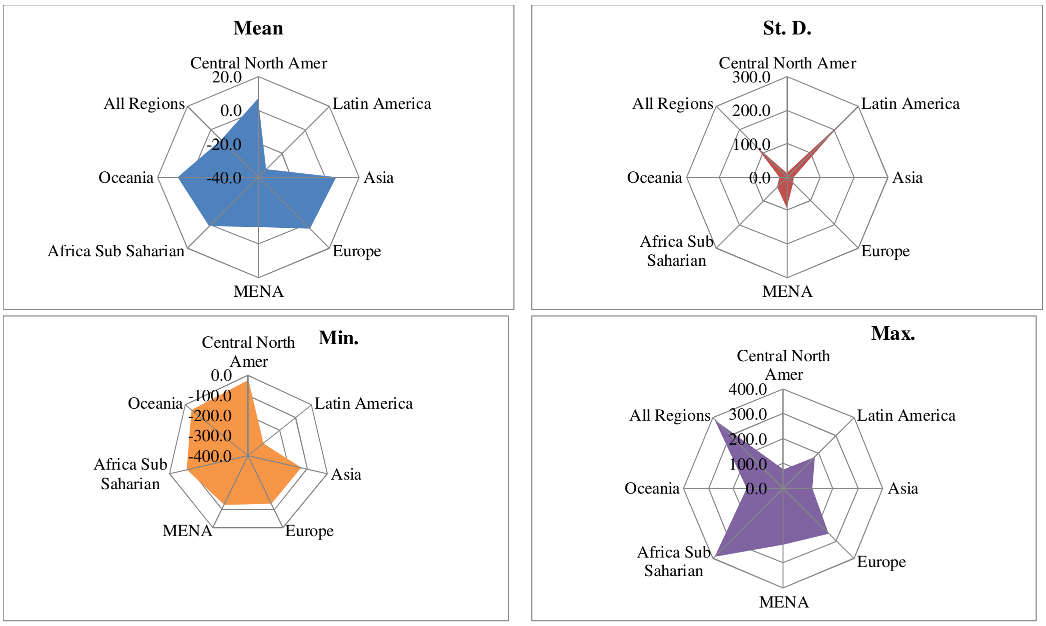

Fig. 4.3 Main stylized facts of growth rate (%) of domestic credit provided by the bank sector along the regional dimension

[82] See appendix H, Table H1, for descriptive statistics of the GDP growth rate data for each country.

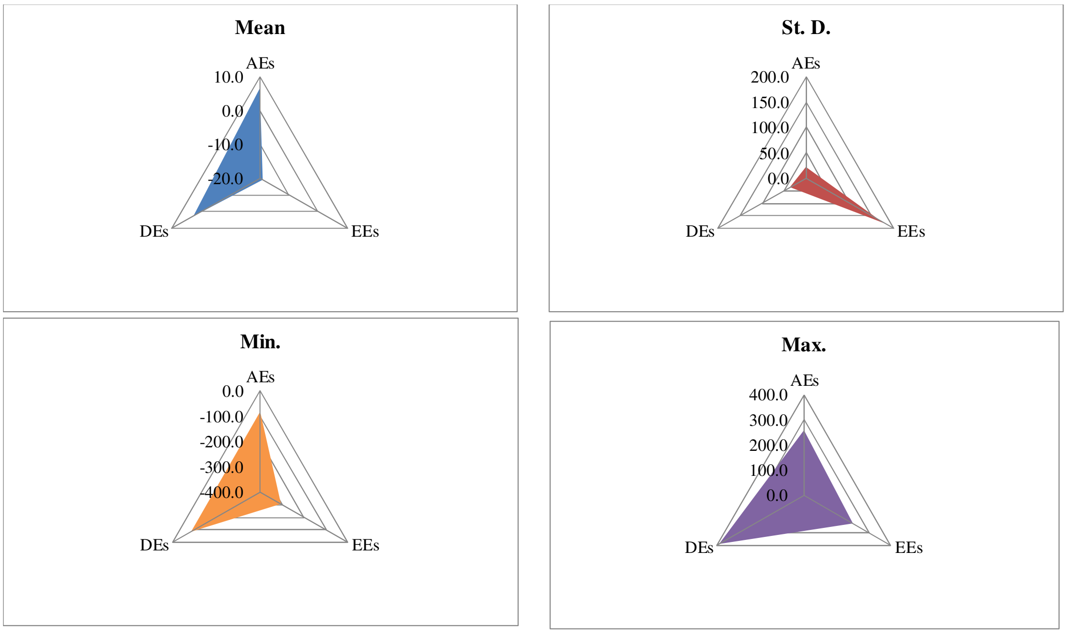

Fig. 4.4 Main stylized facts of growth rate (%) of domestic credit provided by the bank sector along the economic type dimension

If we consider the economic type dimension (see Figure 4.4), we can note that in the AEs countries there is the strongest average growth rate of the credit, instead in the EEs countries the average dynamic of the credit is negative and the standard deviation in the group of EEs countries is very high.

See the Table 4.2 to see the main descriptive statistics for the credit dynamics in sub-group of countries "crossing" the regional and the economic type dimensions[83]. Within the EEs group, the European emerging countries have the worst average rate of credit dynamic, instead in the Latin America emerging countries (where the average dynamic of the credit is negative too) there is the highest standard deviation. Among the AEs, in all regions the average dynamic of the credit is positive, in particular the Asian advanced economy countries have the highest average growth rate; the standard deviation in the European advanced economy is the highest.

Table 4.2 Main stylized facts of domestic credit provided by the banking sector in sub-groups of countries

	Central North America				Latin America				Asia				Europe			
	Mean	St. D.	Min.	Max.	Mean	St. D.	Min.	Max.	Mean	St. D.	Min.	Max.	Mean	St. D.	Min.	Max.
AEs	5.8	11.1	-25.0	75.6	n.a	n.a	n.a	n.a	8.9	14.0	-13.8	-13.8	6.3	23.4	-83.2	257.9
EEs	n.a	n.a	n.a	n.a	-35.0	239.0	-304.7	178.3	6.6	22.3	-130.8	115.6	-38.6	40.0	-134.6	28.8
DEs	9.0	12.4	-13.5	41.3	-1.7	19.8	-49.8	48.2	5.4	13.2	-33.8	53.2	n.a	n.a	n.a	n.a
All Types	6.9	11.6	-25.0	75.6	-33.4	233.4	-304.7	178.3	6.6	20.6	-130.8	115.6	3.7	26.8	-134.6	257.9

	MENA				Africa Sub Saharian				Oceania				All Regions			
	Mean	St. D.	Min.	Max.	Mean	St. D.	Min.	Max.	Mean	St. D.	Min.	Max.	Mean	St. D.	Min.	Max.
AEs	n.a	n.a	n.a	n.a	n.a	n.a	n.a	n.a	8.4	22.8	-32.1	146.8	6.6	22.1	-83.2	257.9
EEs	-10.0	91.9	-126.8	225.9	1.2	31.7	-72.9	211.5	n.a	n.a	n.a	n.a	-18.9	177.4	-304.7	225.9
DEs	n.a.	n.a.	n.a.	n.a.	1.4	44.0	-85.4	389.4	7.0	20.9	-38.7	83.8	2.7	36.7	-85.4	389.4
All Types	-10.0	91.9	-126.8	225.9	1.4	41.2	-85.4	389.4	7.9	22.1	-38.7	146.8	-8.7	133.5	-304.7	389.4

[83] See appendix H, table H2, for descriptive statistics of the credit growth rate data for each country.

Given the heterogeneity of the dataset, as in chapter 3 all the data have been standardized prior to estimation. This makes coherent the equal weighting scheme implicit in the econometric model used for the empirical investigation.

2.2 The approach used to investigate the decoupling hypothesis

2.2.1 The model and the CAs

In this chapter I used the same modelling approach presented in chapter 3, namely a time-varying Panel VAR model with the factorization of coefficients (Canova and Ciccarelli, 2009), estimated on the data presented above and one lag in the predetermined variables.

Three different model specifications were implemented, and the model with the greatest support from the data was used to perform the CA exercises. The model specifications included the global factor, the country-specific factors and the economic variable factors (namely, the GDP factor and the credit factor) in all three models, together with the group factors in the second model or the regional factors in the third model.

Through the CA experiments, the responses of the GDP in the EEs to credit and real shocks (considered separately one at time) coming from the AEs were quantified for different sub-period, and the responses were compared to identify any changes. I followed the same approach explained in the paragraph 2.3.4 of the chapter 3 however, for the convenience of the readers, let me remind that the experiments performed in this work are the differences between two conditional expectations[84]. The first conditional expectation is the one the model, estimated using the data prior to time t when the supposed shock appears[85], would have obtained for the GDP of each country on the time horizon $t + \tau$ ($\tau = 1,2,3$ for example) based on the hypothesis that at time t for each advanced economy the actual growth rate of credit (when you wish to consider the credit shocks) or the growth rate of GDP (when you wish to consider the real shocks) were reduced by 1.0 point. The second conditional expectation of GDP is the one the model would have obtained based on the actual growth rate of credit of each advanced economy at time t (when you wish to consider the credit shocks), or based on the actual growth

[84] The conditional expectations are computed orthogonaling the covariance matrix of the reduced form shocks, assuming that AEs block comes first, a natural choice given the patterns of trade, remittances and capital flows discussed in the first chapter.

[85] Part of the experiments presented in this section have been performed also using the model estimated on the entire data sample (1978-2010); see the appendix J for the details.

rate of GDP of each advanced economy at time t (when you wish to consider the real shocks).

Given the way in which the experiment has been designed, in one case it has been simulated a credit shock which is given by the difference between the counterfactual and the actual credit growth rates of the AEs (namely a negative shock of 1.0 point[86]); in the other case it has been simulated a real shock which is given by the difference between the counterfactual and the actual GDP growth rates of the AEs (namely a negative shock of 1.0 point).

The results of these CA experiments did not have any structural content. For example, it was not possible to determine whether a certain policy had any effect, however this exercise is very useful to the end of this paper as it allows to observe how the resilience of the EEs to adverse scenarios that spread from AEs changed over time.

2.2.2 The priors

In this chapter, the assumptions about the functional form of the probability density functions of parameters are the same as those made in chapter 3 (see appendix D). Even the values of the hyperparameters are the same, with the exception of the hyperparameter z_1; the value of the latter must be chosen in line with the specific characteristics of the model in this chapter. z_1 are the degrees of freedom of the matrix Ω^{-1}, and the matrix Ω with dimension $(NG \times NG)$ is the variance/covariance matrix of the residuals E_t in eq. (3.1) of chapter 3, so Ω^{-1} is the precision matrix. The Wishart distribution[87] is often used as the prior for the precision matrix, however for the Wishart distribution to be proper the degrees of freedom must be[88] at least equal to the dimension of the matrix Ω^{-1}, and so in this chapter the hyperparameter z_1 has been set equal to $156 + 50$ (i.e., dimension of the squared matrix Ω^{-1} plus 50).

For the values of the other hyperparameters, the functional form of the conditional posterior distributions of parameters and the details on the sampling algorithm used to perform estimation in Bayesian framework see the appendix D.

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[86] Let me note that, given that data have been standardized, in all cases I am simulating a 1.0 standard deviation shock. As in chapter 3, it is assumed that the shocks do not affect the law of motion of the coefficients (equation 3.7).

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

[88] See Greenberg (2008) pag. 190.

2.3 Results: time path of the resilience of EEs

In this section, counterfactual analyses have been employed to ascertain whether, and to what degree, the resilience of EEs' GDP to credit and real shocks spreading from the AEs has changed over time. In particular, the following subsection 2.3.1 quantifies the effects of the credit shock spreading from the AEs, by simulating a one-point reduction in credit growth rate in the AEs; whereas the subsection 2.3.2 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 dynamic amounting to one standard deviation. Finally, the subsection 2.3.3 compares 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[89], data provided greater support to the model with the global factor, the variable specific factors and the country-specific factors. Table 4.3 reports the marginal likelihood in logarithmic terms, and the appendix I presents the historical decomposition of fluctuations of GDP and of credit for each country at each point of time into their components, namely the global component, the respective variable component and the idiosyncratic component (the country specific component plus the residual term).

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

Table 4.3 Estimated Log marginal likelihood of models.

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

2.3.1 Spread of credit shocks from the AEs to the EEs

For each year in the period between 1991 and 2010, a calculation was made of the effect that a credit squeeze in the AEs has on the GDP of the EEs (see Table 4.4).

[89] Marginal likelihoods are computed as harmonic mean (Newton and Raftery, 1994).

The cumulated median impact, shown in the last column of Table 4.4 and also graphically in Figure 4.5 panel 1, have fallen over the last twenty years; in fact, in the sub-period 2001-2010 they were estimated to be about 40% lower than they were over the previous ten years (1991-2000).

A more detailed inspection of the results (Figure 4.5 panel 2) puts in evidence that the EEs' resilience to external credit shocks worsened from the 1991-1995 to 1996-2000, as median impact reached its nadir in the second half of 1990s. However, thereafter the EEs' resilience improved and in the period 2006-2010 the cumulated median impact on GDP was lower (around 85%) than it had been during the period 1996-2000.

Table 4.4 Dynamic impact of the credit shock spreading from AEs to Emerging Economies

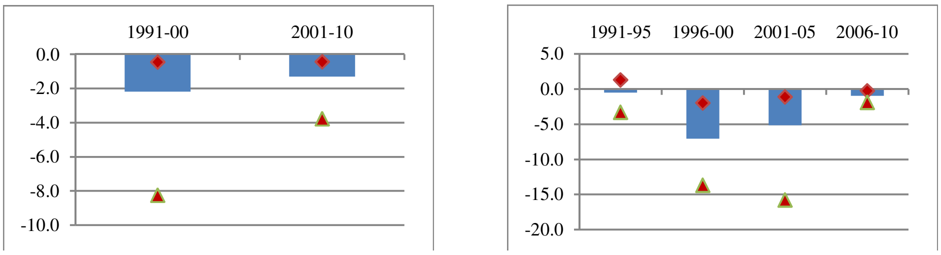
	t+1			*t+2*			*t+3*			*t+4*			cumulated median impact		
	U	M	L	U	M	L	U	M	L	U	M	L	U	M	L
1991-2000	0.01	-0.04	-0.11	0.22	0.09	-0.03	-0.34	-1.03	-2.23	-0.35	-1.20	-5.88	-0.46	-2.19	-8.25
2001-2010	0.01	-0.17	-0.38	-0.08	-0.21	-0.39	-0.25	-0.57	-1.09	-0.11	-0.35	-1.90	-0.43	-1.31	-3.76
Subsamples															
1991-1995	0.02	-0.02	-0.07	0.08	-0.02	-0.11	0.07	-0.29	-1.03	1.14	-0.16	-2.08	1.31	-0.49	-3.29
1996-2000	0.00	-0.07	-0.17	0.36	0.22	0.09	-1.04	-1.96	-3.20	-1.29	-5.26	-10.40	-1.96	-7.07	-13.67
2001-2005	0.01	-0.12	-0.30	-0.14	-0.34	-0.62	-0.37	-0.80	-1.48	-0.61	-3.86	-13.38	-1.10	-5.13	-15.78
2006-2010	-0.01	-0.23	-0.46	-0.04	-0.15	-0.27	-0.20	-0.40	-0.83	0.01	-0.16	-0.30	-0.23	-0.94	-1.87

Note: M stands for median, L and U stand for lower and upper values (16^{th} and the 84^{th} percentiles, respectively).

In order to ascertain whether the abovementioned results also reflect evidence to be found at the geographical level, the EEs have been divided on the basis of their respective geographical areas (Latin American, Asian, MENA, and SSA), see Table 4.5.

The force of the cumulated impact (also shown graphically in Figure 4.6, panels 1 to 4) reveals an interesting result. Regional characteristic matter, in fact, while in Latin American EEs and Asian EEs the resilience has improved from 1990s to 2000s, in the same period for MENA EEs and SSA EEs it has worsened.

These findings are confirmed by the additional results presented in the appendix J.



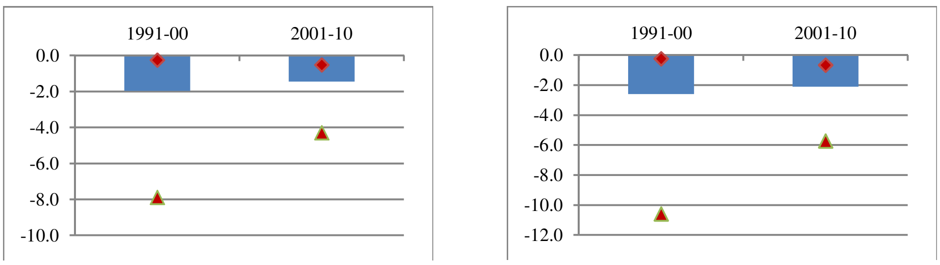
1. 2.

Fig. 4.5 Cumulated (median, 16th and the 84th percentiles) impact of the credit shock spreading from AEs to EEs

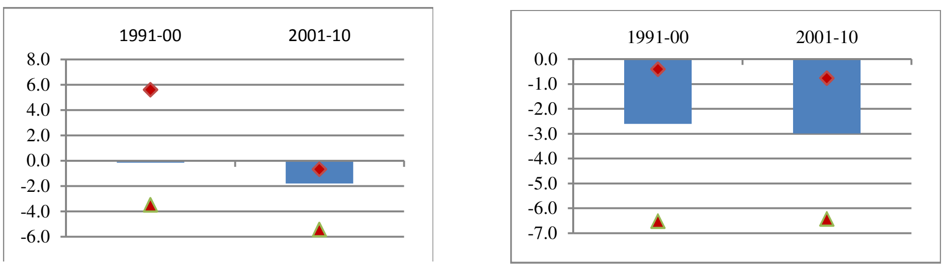
Table 4.5 Dynamic impact of the adverse credit scenario in AEs grouped on the basis of their geographical areas

	t+1			*t+2*			*t+3*			*t+4*			cumulated median impact		
	U	M	L	U	M	L	U	M	L	U	M	L	U	M	L
Latin America															
1991-2000	0.01	-0.03	-0.11	0.22	0.09	-0.03	-0.25	-0.84	-2.08	-0.23	-1.19	-5.65	-0.24	-1.97	-7.88
2001-2010	0.00	-0.18	-0.39	-0.09	-0.22	-0.41	-0.29	-0.64	-1.22	-0.14	-0.40	-2.27	-0.52	-1.45	-4.28
Asia															
1991-2000	0.01	-0.04	-0.13	0.26	0.10	-0.02	-0.41	-1.16	-2.68	-0.10	-1.49	-7.76	-0.24	-2.60	-10.59
2001-2010	-0.01	-0.20	-0.41	-0.13	-0.28	-0.48	-0.28	-0.60	-1.13	-0.25	-1.03	-3.70	-0.66	-2.10	-5.73
MENA															
1991-2000	0.01	-0.04	-0.13	0.24	0.07	-0.03	-0.45	-1.23	-2.88	5.83	1.06	-0.41	5.63	-0.14	-3.46
2001-2010	-0.01	-0.20	-0.41	-0.12	-0.27	-0.46	-0.29	-0.60	-1.14	-0.24	-0.71	-3.40	-0.65	-1.78	-5.42
SSA															
1991-2000	0.00	-0.05	-0.12	0.21	0.09	0.02	-0.52	-1.16	-2.49	-0.09	-1.47	-3.92	-0.40	-2.60	-6.52
2001-2010	-0.01	-0.22	-0.43	-0.19	-0.35	-0.56	-0.25	-0.56	-1.06	-0.31	-1.86	-4.38	-0.76	-2.99	-6.43

Note: M stands for median, L and U stand for lower and upper values (16th and the 84th percentiles, respectively).



1. Latin America EEs 2. Asia EEs



3. MENA EEs 4. SSA EEs

Fig. 4.6 Cumulated (median, 16th and 84th percentiles) impact of the credit shock spreading from AEs to EEs grouped by regions

2.3.2 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 to simulate a credit shock, a real shock was taken into consideration.

Table 4.6 Dynamic impact of the real shock spreading from AEs to Emerging Economies

	t+1			*t+2*			*t+3*			*t+4*			cumulated median impact		
	U	M	L	U	M	L	U	M	L	U	M	L	U	M	L
1991-2000	-0.01	-0.09	-0.20	0.25	0.07	-0.08	-0.28	-1.15	-2.41	1.22	-0.93	-6.37	1.19	-2.10	-9.06
2001-2010	0.12	-0.05	-0.29	0.01	-0.11	-0.24	0.64	0.19	0.01	-0.12	-0.44	-1.59	0.65	-0.41	-2.10
Subsamples															
1991-1995	0.00	-0.07	-0.18	0.44	0.24	0.05	-1.74	-3.15	-5.64	-0.90	-3.34	-8.15	-2.20	-6.32	-13.92
1996-2000	-0.02	-0.10	-0.23	0.08	-0.05	-0.22	0.29	-0.20	-0.83	0.94	-2.22	-9.60	1.30	-2.58	-10.88
2001-2005	0.12	-0.03	-0.24	0.07	-0.07	-0.22	0.58	0.10	-0.27	-0.39	-2.95	-8.74	0.38	-2.94	-9.47
2006-2010	0.12	-0.09	-0.32	-0.04	-0.14	-0.26	0.71	0.26	0.07	-0.07	-0.26	-0.45	0.71	-0.22	-0.96

Note: M stands for median, L and U stand for lower and upper values (16th and the 84th percentiles, respectively).

Table 4.6 shows the median impact for the entire group of EEs, calculated for different periods of time. The analysis of the immediate impact effect reveals that the degree of the impact on the EEs of the simulated AEs' real shock over the last ten years was lower than that recorded during the previous ten years (see Figure 4.7 panel 1 and the relative column in Table 4.6). In order to obtain more detailed information, the entire

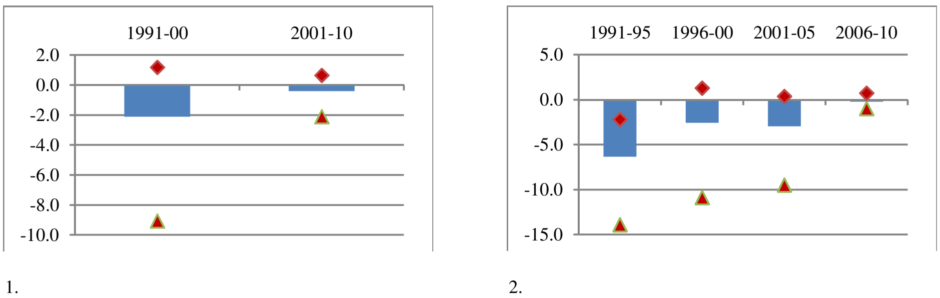
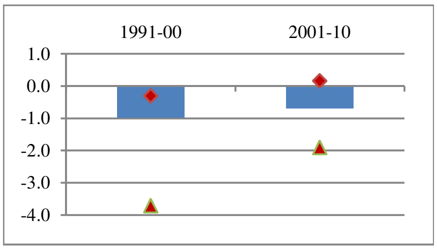
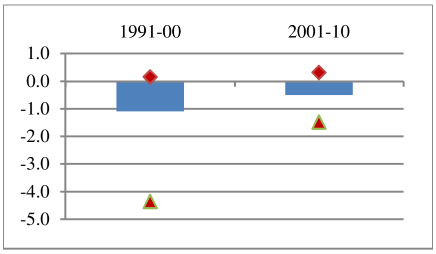


Fig. 4.7 Cumulated (median, 16th and the 84th percentiles) impact of the real shock spreading from AEs to EEs

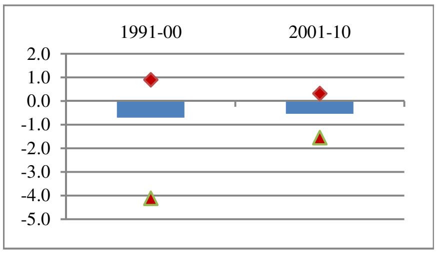
sample period was broken down into five-year sub-periods, and as with the analysis of the credit shock, also in the case of real shock the results that emerge are rather interesting. The EEs' resilience worsened from the five years 1996-2000 to the following five years 2001-2005, however it came back improving substantially thereafter, and in the sub period 2006-2010 it resulted better than all previous sub-periods (Figure 4.7, panel 2).



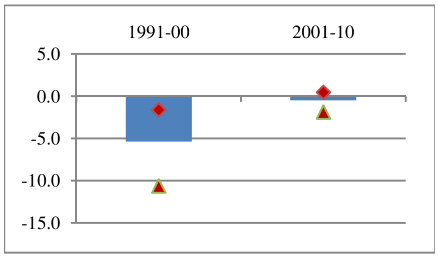
1. Latin America EEs



2. Asia EEs



3. MENA EEs



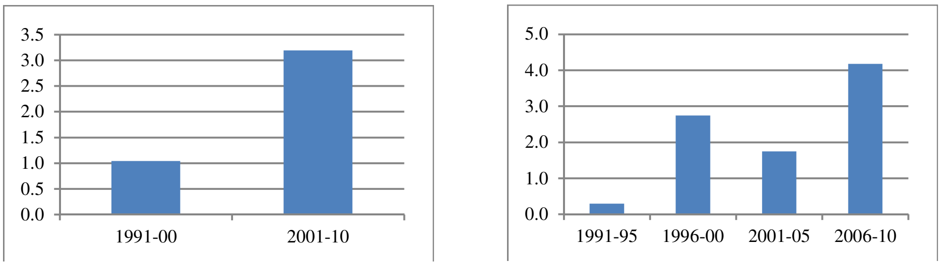
4. SSA EEs

Fig. 4.8 Cumulated (median, 16th and the 84th percentiles) impact of the real shock spreading from AEs to EEs grouped by regions

In geographical terms, that is, by sub-dividing the EEs into geographical areas, what emerges (see Figure 4.8 from panel 1 to 4) is that for all regions the magnitude of the cumulated impact has been lower in recent years than it was in previous years. If we compare the last ten years of the sample period with the previous ten years, the magnitude of the cumulated impact is estimated to have fallen at a rate ranging from 23% in the MENA EEs to about 90% in the SSA EEs (and at rates of 30% in the Latin American EEs and of 54% in the Asian EEs). See the appendix J for additional results.

2.3.3 What type of external shock are EEs more sensible to?

The emerging economies' resilience to external shocks, be they financial or real, seems to have improved in more recent years compared with the initial period of economic globalization. Obviously, this does not mean that the emerging economies have become immune to the effects of any external shocks. Although with a lower degree of vulnerability with respect to the past, the EEs are still sensible to external shocks. At this point, it is natural to demand what kind of external shock – credit or real – such emerging economies are more sensible to. The ratios of credit shock's impacts on the real shock's impacts have been computed. Two interesting results emerge with regard to this question. First, starting from the second half of 1990s, the emerging economies have become more

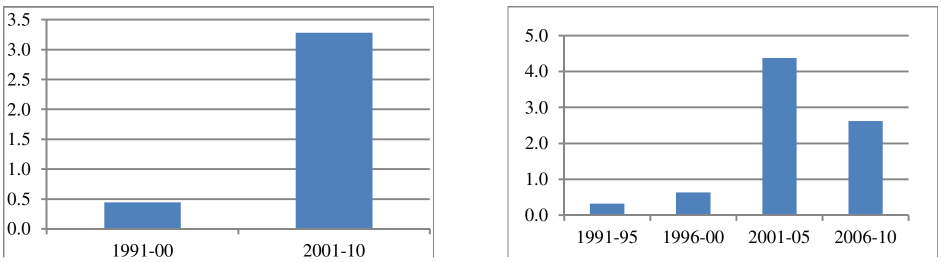


1. 2.

Fig. 4.9 Ratio of cumulated impact of credit shock on cumulated impact of real shock

vulnerable to financial shocks than to real shocks. Second, the greater relative vulnerability to financial shocks was particularly evident during the last five years of the sample period (2006-2010), when the cumulated impact of the simulated external credit shock was more than four times greater than the impact of the simulated external real shock (see Figure 4.9, panel 2), whereas during the early 2000s this multiplying factor was about 1.5, and it was about 2.5 at the end of 1990s.

The greater vulnerability to credit shocks can be seen not only in the cumulated impact, but also in the immediate impact (see Figure 4.10, panels 1 and 2).



1. 2.

Fig. 4.10 Ratio of immediate impact of credit shock on immediate impact of real shock

3. Conclusion

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 cumulated impact of the simulated external credit shock on the emerging economies was 85% lower than the median cumulated impact calculated for the five-year period 1996-2000 (and said impact was around 90% lower in the case of the simulated real shocks).

In general it appears clear that at the present moment in time, EEs are more resilient to adverse scenarios affecting 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). However, in line with the results discussed in the chapter 3, also from the results of the present chapter it arises that the degree of resilience of the EEs 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.

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. However some regional peculiarities emerge. If we compare the last ten years of the sample period with the previous ten years, the magnitude of the cumulated impact of the real credit shock is estimated to have fallen at rate ranging from 23% in the MENA EEs to 91% in SSA EEs, but the more evident heterogeneity among regions is observed in the case of the credit shock; in this case, while in Latin American EEs and Asian EEs the resilience has improved from 1990s to 2000s, in that same period for MENA EEs and SSA EEs it worsened.

To conclude this chapter, two further interesting results should be pointed out here. Starting from about the end of 1990s EEs have become more sensible to credit shocks than to real shocks; moreover, this greater relative vulnerability reached its peak in the last five years of the sample period (i.e. in the years 2006-10), when the cumulated impact of the simulated external credit shock was more than four times greater than the impact of the simulated external real shock.

Appendix G. Set of countries

Table G.1 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 H. Main descriptive statistics

Table H1 Descriptive statistics of GDP growth rate (%) data for each country

Statistics on Series	Argentina		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	1.309	Variance	26.955
Standard Error	5.192	of Sample Mean	0.904
t-Statistic (Mean=0)	1.449	Signif Level	0.157
Skewness	-0.478	Signif Level (Sk=0)	0.284
Kurtosis (excess)	-0.993	Signif Level (Ku=0)	0.297
Jarque-Bera	2.613	Signif Level (JB=0)	0.271

Statistics on Series	Antigua		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	3.183	Variance	31.734
Standard Error	5.633	of Sample Mean	0.981
t-Statistic (Mean=0)	3.246	Signif Level	0.003
Skewness	0.241	Signif Level (Sk=0)	0.589
Kurtosis (excess)	0.361	Signif Level (Ku=0)	0.704
Jarque-Bera	0.499	Signif Level (JB=0)	0.779

Statistics on Series	Australia		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	2.171	Variance	2.367
Standard Error	1.539	of Sample Mean	0.268
t-Statistic (Mean=0)	8.107	Signif Level	0.000
Skewness	-1.352	Signif Level (Sk=0)	0.002
Kurtosis (excess)	2.399	Signif Level (Ku=0)	0.012
Jarque-Bera	17.960	Signif Level (JB=0)	0.000

Statistics on Series	Austria		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	1.894	Variance	3.972
Standard Error	1.993	of Sample Mean	0.347
t-Statistic (Mean=0)	5.458	Signif Level	0.000
Skewness	-0.135	Signif Level (Sk=0)	0.763
Kurtosis (excess)	4.446	Signif Level (Ku=0)	0.000
Jarque-Bera	27.284	Signif Level (JB=0)	0.000

Statistics on Series	Burundi		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	-0.783	Variance	18.447
Standard Error	4.295	of Sample Mean	0.748
t-Statistic (Mean=0)	-1.047	Signif Level	0.303
Skewness	-0.897	Signif Level (Sk=0)	0.045
Kurtosis (excess)	1.980	Signif Level (Ku=0)	0.037
Jarque-Bera	9.814	Signif Level (JB=0)	0.007

Statistics on Series	Belgium		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	1.839	Variance	3.816
Standard Error	1.953	of Sample Mean	0.340
t-Statistic (Mean=0)	5.407	Signif Level	0.000
Skewness	-0.846	Signif Level (Sk=0)	0.058
Kurtosis (excess)	1.252	Signif Level (Ku=0)	0.188
Jarque-Bera	6.092	Signif Level (JB=0)	0.048

Statistics on Series	Iran		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	-0.267	Variance	59.795
Standard Error	7.733	of Sample Mean	1.346
t-Statistic (Mean=0)	-0.198	Signif Level	0.844
Skewness	-0.837	Signif Level (Sk=0)	0.061
Kurtosis (excess)	0.143	Signif Level (Ku=0)	0.880
Jarque-Bera	3.883	Signif Level (JB=0)	0.144

Statistics on Series	Iceland		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	0.817	Variance	24.597
Standard Error	4.960	of Sample Mean	0.863
t-Statistic (Mean=0)	0.947	Signif Level	0.351
Skewness	-0.545	Signif Level (Sk=0)	0.222
Kurtosis (excess)	2.010	Signif Level (Ku=0)	0.035
Jarque-Bera	7.189	Signif Level (JB=0)	0.027

Statistics on Series	Israel		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	1.815	Variance	6.285
Standard Error	2.507	of Sample Mean	0.436
t-Statistic (Mean=0)	4.159	Signif Level	0.000
Skewness	-0.148	Signif Level (Sk=0)	0.741
Kurtosis (excess)	-0.483	Signif Level (Ku=0)	0.612
Jarque-Bera	0.441	Signif Level (JB=0)	0.802

Statistics on Series	Italy		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	1.570	Variance	5.193
Standard Error	2.279	of Sample Mean	0.397
t-Statistic (Mean=0)	3.957	Signif Level	0.000
Skewness	-1.075	Signif Level (Sk=0)	0.016
Kurtosis (excess)	3.674	Signif Level (Ku=0)	0.000
Jarque-Bera	24.920	Signif Level (JB=0)	0.000

Statistics on Series	Jordania		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	1.659	Variance	42.939
Standard Error	6.553	of Sample Mean	1.141
t-Statistic (Mean=0)	1.455	Signif Level	0.155
Skewness	-0.409	Signif Level (Sk=0)	0.361
Kurtosis (excess)	1.294	Signif Level (Ku=0)	0.174
Jarque-Bera	3.221	Signif Level (JB=0)	0.200

Statistics on Series	Japan		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	1.941	Variance	7.136
Standard Error	2.671	of Sample Mean	0.465
t-Statistic (Mean=0)	4.174	Signif Level	0.000
Skewness	-1.061	Signif Level (Sk=0)	0.018
Kurtosis (excess)	2.926	Signif Level (Ku=0)	0.002
Jarque-Bera	17.965	Signif Level (JB=0)	0.000

Table H1 Continue

Statistics on Series	Benin		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	1.262	Variance	33.423
Standard Error	5.781	of Sample Mean	1.006
t-Statistic (Mean=0)	1.254	Signif Level	0.219
Skewness	1.451	Signif Level (Sk=0)	0.001
Kurtosis (excess)	5.744	Signif Level (Ku=0)	0.000
Jarque-Bera	56.947	Signif Level (JB=0)	0.000

Statistics on Series	Kenia		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	0.566	Variance	9.764
Standard Error	3.125	of Sample Mean	0.544
t-Statistic (Mean=0)	1.041	Signif Level	0.306
Skewness	0.431	Signif Level (Sk=0)	0.334
Kurtosis (excess)	-0.013	Signif Level (Ku=0)	0.989
Jarque-Bera	1.023	Signif Level (JB=0)	0.600

Statistics on Series	Burkina Faso		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	1.272	Variance	13.734
Standard Error	3.706	of Sample Mean	0.645
t-Statistic (Mean=0)	1.972	Signif Level	0.057
Skewness	-0.286	Signif Level (Sk=0)	0.522
Kurtosis (excess)	-0.132	Signif Level (Ku=0)	0.889
Jarque-Bera	0.474	Signif Level (JB=0)	0.789

Statistics on Series	Korea Rep		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	5.596	Variance	22.706
Standard Error	4.765	of Sample Mean	0.829
t-Statistic (Mean=0)	6.746	Signif Level	0.000
Skewness	-1.613	Signif Level (Sk=0)	0.000
Kurtosis (excess)	3.683	Signif Level (Ku=0)	0.000
Jarque-Bera	32.969	Signif Level (JB=0)	0.000

Statistics on Series	Bangladesh		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	2.403	Variance	6.488
Standard Error	2.547	of Sample Mean	0.443
t-Statistic (Mean=0)	5.419	Signif Level	0.000
Skewness	-0.360	Signif Level (Sk=0)	0.420
Kurtosis (excess)	0.143	Signif Level (Ku=0)	0.881
Jarque-Bera	0.743	Signif Level (JB=0)	0.690

Statistics on Series	Sri Lanka		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	4.218	Variance	14.560
Standard Error	3.816	of Sample Mean	0.664
t-Statistic (Mean=0)	6.350	Signif Level	0.000
Skewness	1.076	Signif Level (Sk=0)	0.016
Kurtosis (excess)	3.673	Signif Level (Ku=0)	0.000
Jarque-Bera	24.920	Signif Level (JB=0)	0.000

Statistics on Series	Bahrain		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	-0.598	Variance	42.843
Standard Error	6.545	of Sample Mean	1.139
t-Statistic (Mean=0)	-0.525	Signif Level	0.603
Skewness	-1.928	Signif Level (Sk=0)	0.000
Kurtosis (excess)	4.909	Signif Level (Ku=0)	0.000
Jarque-Bera	53.575	Signif Level (JB=0)	0.000

Statistics on Series	Luxembourg		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	3.324	Variance	12.303
Standard Error	3.508	of Sample Mean	0.611
t-Statistic (Mean=0)	5.444	Signif Level	0.000
Skewness	-0.489	Signif Level (Sk=0)	0.274
Kurtosis (excess)	1.295	Signif Level (Ku=0)	0.173
Jarque-Bera	3.621	Signif Level (JB=0)	0.164

Statistics on Series	Bahamas		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	1.820	Variance	25.798
Standard Error	5.079	of Sample Mean	0.884
t-Statistic (Mean=0)	2.058	Signif Level	0.048
Skewness	0.353	Signif Level (Sk=0)	0.430
Kurtosis (excess)	0.740	Signif Level (Ku=0)	0.437
Jarque-Bera	1.437	Signif Level (JB=0)	0.488

Statistics on Series	Morocco		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	1.790	Variance	24.630
Standard Error	4.963	of Sample Mean	0.864
t-Statistic (Mean=0)	2.072	Signif Level	0.046
Skewness	-0.460	Signif Level (Sk=0)	0.304
Kurtosis (excess)	-0.732	Signif Level (Ku=0)	0.442
Jarque-Bera	1.898	Signif Level (JB=0)	0.387

Statistics on Series	Belize		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	2.246	Variance	24.074
Standard Error	4.907	of Sample Mean	0.854
t-Statistic (Mean=0)	2.630	Signif Level	0.013
Skewness	0.363	Signif Level (Sk=0)	0.417
Kurtosis (excess)	-0.897	Signif Level (Ku=0)	0.346
Jarque-Bera	1.829	Signif Level (JB=0)	0.401

Statistics on Series	Madagascar		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	-1.357	Variance	16.449
Standard Error	4.056	of Sample Mean	0.706
t-Statistic (Mean=0)	-1.922	Signif Level	0.064
Skewness	-1.783	Signif Level (Sk=0)	0.000
Kurtosis (excess)	5.389	Signif Level (Ku=0)	0.000
Jarque-Bera	57.415	Signif Level (JB=0)	0.000

Table H1 Continue

Statistics on Series	Brazil		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	1.018	Variance	13.478
Standard Error	3.671	of Sample Mean	0.639
t-Statistic (Mean=0)	1.594	Signif Level	0.121
Skewness	-0.260	Signif Level (Sk=0)	0.561
Kurtosis (excess)	0.774	Signif Level (Ku=0)	0.416
Jarque-Bera	1.196	Signif Level (JB=0)	0.550

Statistics on Series	Barbados		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	0.643	Variance	20.247
Standard Error	4.500	of Sample Mean	0.783
t-Statistic (Mean=0)	0.821	Signif Level	0.418
Skewness	-0.605	Signif Level (Sk=0)	0.176
Kurtosis (excess)	0.543	Signif Level (Ku=0)	0.568
Jarque-Bera	2.418	Signif Level (JB=0)	0.298

Statistics on Series	Canada		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	1.584	Variance	5.693
Standard Error	2.386	of Sample Mean	0.415
t-Statistic (Mean=0)	3.814	Signif Level	0.001
Skewness	-1.097	Signif Level (Sk=0)	0.014
Kurtosis (excess)	1.173	Signif Level (Ku=0)	0.218
Jarque-Bera	8.508	Signif Level (JB=0)	0.014

Statistics on Series	China ver2		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	6.730	Variance	12.797
Standard Error	3.577	of Sample Mean	0.623
t-Statistic (Mean=0)	10.808	Signif Level	0.000
Skewness	-0.277	Signif Level (Sk=0)	0.536
Kurtosis (excess)	-0.155	Signif Level (Ku=0)	0.870
Jarque-Bera	0.454	Signif Level (JB=0)	0.797

Statistics on Series	Chile		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	3.640	Variance	27.058
Standard Error	5.202	of Sample Mean	0.906
t-Statistic (Mean=0)	4.020	Signif Level	0.000
Skewness	-2.217	Signif Level (Sk=0)	0.000
Kurtosis (excess)	7.338	Signif Level (Ku=0)	0.000
Jarque-Bera	101.061	Signif Level (JB=0)	0.000

Statistics on Series	Cameroon		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	-0.141	Variance	24.680
Standard Error	4.968	of Sample Mean	0.865
t-Statistic (Mean=0)	-0.163	Signif Level	0.871
Skewness	0.913	Signif Level (Sk=0)	0.041
Kurtosis (excess)	3.637	Signif Level (Ku=0)	0.000
Jarque-Bera	22.772	Signif Level (JB=0)	0.000

Statistics on Series	Mexico		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	1.174	Variance	20.801
Standard Error	4.561	of Sample Mean	0.794
t-Statistic (Mean=0)	1.479	Signif Level	0.149
Skewness	-1.034	Signif Level (Sk=0)	0.021
Kurtosis (excess)	0.550	Signif Level (Ku=0)	0.563
Jarque-Bera	6.298	Signif Level (JB=0)	0.043

Statistics on Series	Mali		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	1.965	Variance	25.823
Standard Error	5.082	of Sample Mean	0.885
t-Statistic (Mean=0)	2.221	Signif Level	0.034
Skewness	0.157	Signif Level (Sk=0)	0.726
Kurtosis (excess)	0.837	Signif Level (Ku=0)	0.379
Jarque-Bera	1.099	Signif Level (JB=0)	0.577

Statistics on Series	Mauritius		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	3.385	Variance	18.448
Standard Error	4.295	of Sample Mean	0.748
t-Statistic (Mean=0)	4.527	Signif Level	0.000
Skewness	-2.773	Signif Level (Sk=0)	0.000
Kurtosis (excess)	12.002	Signif Level (Ku=0)	0.000
Jarque-Bera	240.360	Signif Level (JB=0)	0.000

Statistics on Series	Malaysia		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	3.841	Variance	20.417
Standard Error	4.518	of Sample Mean	0.787
t-Statistic (Mean=0)	4.883	Signif Level	0.000
Skewness	-1.564	Signif Level (Sk=0)	0.000
Kurtosis (excess)	2.428	Signif Level (Ku=0)	0.011
Jarque-Bera	21.551	Signif Level (JB=0)	0.000

Statistics on Series	Nigeria		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	0.013	Variance	55.854
Standard Error	7.474	of Sample Mean	1.301
t-Statistic (Mean=0)	0.010	Signif Level	0.992
Skewness	0.178	Signif Level (Sk=0)	0.691
Kurtosis (excess)	-0.446	Signif Level (Ku=0)	0.639
Jarque-Bera	0.446	Signif Level (JB=0)	0.800

Statistics on Series	Netherlands		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	1.545	Variance	4.078
Standard Error	2.019	of Sample Mean	0.352
t-Statistic (Mean=0)	4.394	Signif Level	0.000
Skewness	-1.475	Signif Level (Sk=0)	0.001
Kurtosis (excess)	2.386	Signif Level (Ku=0)	0.012
Jarque-Bera	19.790	Signif Level (JB=0)	0.000

Table H1 Continue

Statistics on Series	Colombia		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	1.605	Variance	6.069
Standard Error	2.464	of Sample Mean	0.429
t-Statistic (Mean=0)	3.741	Signif Level	0.001
Skewness	-0.944	Signif Level (Sk=0)	0.035
Kurtosis (excess)	2.902	Signif Level (Ku=0)	0.002
Jarque-Bera	16.481	Signif Level (JB=0)	0.000

Statistics on Series	Costa Rica		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	1.167	Variance	13.325
Standard Error	3.650	of Sample Mean	0.635
t-Statistic (Mean=0)	1.837	Signif Level	0.076
Skewness	-1.381	Signif Level (Sk=0)	0.002
Kurtosis (excess)	2.960	Signif Level (Ku=0)	0.002
Jarque-Bera	22.533	Signif Level (JB=0)	0.000

Statistics on Series	Dominica		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	3.312	Variance	23.772
Standard Error	4.876	of Sample Mean	0.849
t-Statistic (Mean=0)	3.902	Signif Level	0.000
Skewness	-0.650	Signif Level (Sk=0)	0.145
Kurtosis (excess)	2.345	Signif Level (Ku=0)	0.014
Jarque-Bera	9.891	Signif Level (JB=0)	0.007

Statistics on Series	Denmark		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	1.573	Variance	5.938
Standard Error	2.437	of Sample Mean	0.424
t-Statistic (Mean=0)	3.709	Signif Level	0.001
Skewness	-1.109	Signif Level (Sk=0)	0.013
Kurtosis (excess)	3.434	Signif Level (Ku=0)	0.000
Jarque-Bera	22.977	Signif Level (JB=0)	0.000

Statistics on Series	Dominican Rep		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	2.876	Variance	16.439
Standard Error	4.054	of Sample Mean	0.706
t-Statistic (Mean=0)	4.075	Signif Level	0.000
Skewness	-0.247	Signif Level (Sk=0)	0.580
Kurtosis (excess)	-0.208	Signif Level (Ku=0)	0.827
Jarque-Bera	0.395	Signif Level (JB=0)	0.821

Statistics on Series	Ecuador		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	0.919	Variance	14.113
Standard Error	3.757	of Sample Mean	0.654
t-Statistic (Mean=0)	1.405	Signif Level	0.170
Skewness	-1.191	Signif Level (Sk=0)	0.008
Kurtosis (excess)	1.576	Signif Level (Ku=0)	0.098
Jarque-Bera	11.209	Signif Level (JB=0)	0.004

Statistics on Series	Nepal		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	2.076	Variance	12.000
Standard Error	3.464	of Sample Mean	0.603
t-Statistic (Mean=0)	3.442	Signif Level	0.002
Skewness	-0.035	Signif Level (Sk=0)	0.937
Kurtosis (excess)	0.386	Signif Level (Ku=0)	0.685
Jarque-Bera	0.212	Signif Level (JB=0)	0.899

Statistics on Series	New Zealand		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	1.438	Variance	3.252
Standard Error	1.803	of Sample Mean	0.314
t-Statistic (Mean=0)	4.581	Signif Level	0.000
Skewness	-0.112	Signif Level (Sk=0)	0.802
Kurtosis (excess)	-0.404	Signif Level (Ku=0)	0.671
Jarque-Bera	0.293	Signif Level (JB=0)	0.864

Statistics on Series	Oman		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	2.624	Variance	31.611
Standard Error	5.622	of Sample Mean	0.979
t-Statistic (Mean=0)	2.681	Signif Level	0.012
Skewness	-0.308	Signif Level (Sk=0)	0.490
Kurtosis (excess)	1.214	Signif Level (Ku=0)	0.202
Jarque-Bera	2.550	Signif Level (JB=0)	0.279

Statistics on Series	Pakistan		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	2.446	Variance	4.960
Standard Error	2.227	of Sample Mean	0.388
t-Statistic (Mean=0)	6.309	Signif Level	0.000
Skewness	0.698	Signif Level (Sk=0)	0.118
Kurtosis (excess)	1.230	Signif Level (Ku=0)	0.196
Jarque-Bera	4.760	Signif Level (JB=0)	0.093

Statistics on Series	Panama		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	3.132	Variance	28.527
Standard Error	5.341	of Sample Mean	0.930
t-Statistic (Mean=0)	3.369	Signif Level	0.002
Skewness	0.814	Signif Level (Sk=0)	0.068
Kurtosis (excess)	2.886	Signif Level (Ku=0)	0.002
Jarque-Bera	15.100	Signif Level (JB=0)	0.001

Statistics on Series	Philippines		
Annual Data From 1978:01 To 2010:01			
Observations	33		
Sample Mean	1.032	Variance	13.732
Standard Error	3.706	of Sample Mean	0.645
t-Statistic (Mean=0)	1.601	Signif Level	0.119
Skewness	-1.830	Signif Level (Sk=0)	0.000
Kurtosis (excess)	3.578	Signif Level (Ku=0)	0.000
Jarque-Bera	36.020	Signif Level (JB=0)	0.000

Table H1 Continue

Statistics on Series	Egypt		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	4.178	Variance	9.643
Standard Error	3.105	of Sample Mean	0.541
t-Statistic (Mean=0)	7.729	Signif Level	0.000
Skewness	1.979	Signif Level (Sk=0)	0.000
Kurtosis (excess)	6.815	Signif Level (Ku=0)	0.000
Jarque-Bera	85.387	Signif Level (JB=0)	0.000

Statistics on Series	Portugal		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	2.096	Variance	9.658
Standard Error	3.108	of Sample Mean	0.541
t-Statistic (Mean=0)	3.874	Signif Level	0.000
Skewness	-0.119	Signif Level (Sk=0)	0.789
Kurtosis (excess)	0.029	Signif Level (Ku=0)	0.975
Jarque-Bera	0.080	Signif Level (JB=0)	0.961

Statistics on Series	Spain		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	1.745	Variance	5.308
Standard Error	2.304	of Sample Mean	0.401
t-Statistic (Mean=0)	4.350	Signif Level	0.000
Skewness	-0.667	Signif Level (Sk=0)	0.135
Kurtosis (excess)	1.066	Signif Level (Ku=0)	0.262
Jarque-Bera	4.009	Signif Level (JB=0)	0.135

Statistics on Series	Paraguay		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	1.082	Variance	19.910
Standard Error	4.462	of Sample Mean	0.777
t-Statistic (Mean=0)	1.392	Signif Level	0.173
Skewness	1.295	Signif Level (Sk=0)	0.004
Kurtosis (excess)	2.616	Signif Level (Ku=0)	0.006
Jarque-Bera	18.634	Signif Level (JB=0)	0.000

Statistics on Series	Finlandia		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	2.212	Variance	16.343
Standard Error	4.043	of Sample Mean	0.704
t-Statistic (Mean=0)	3.143	Signif Level	0.004
Skewness	-1.616	Signif Level (Sk=0)	0.000
Kurtosis (excess)	3.003	Signif Level (Ku=0)	0.002
Jarque-Bera	26.758	Signif Level (JB=0)	0.000

Statistics on Series	Singapore		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	5.022	Variance	23.950
Standard Error	4.894	of Sample Mean	0.852
t-Statistic (Mean=0)	5.894	Signif Level	0.000
Skewness	-0.716	Signif Level (Sk=0)	0.109
Kurtosis (excess)	0.436	Signif Level (Ku=0)	0.647
Jarque-Bera	3.082	Signif Level (JB=0)	0.214

Statistics on Series	Fiji		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	0.873	Variance	22.604
Standard Error	4.754	of Sample Mean	0.828
t-Statistic (Mean=0)	1.055	Signif Level	0.299
Skewness	0.461	Signif Level (Sk=0)	0.302
Kurtosis (excess)	0.553	Signif Level (Ku=0)	0.561
Jarque-Bera	1.590	Signif Level (JB=0)	0.452

Statistics on Series	El Salvador		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	0.649	Variance	13.726
Standard Error	3.705	of Sample Mean	0.645
t-Statistic (Mean=0)	1.006	Signif Level	0.322
Skewness	-1.089	Signif Level (Sk=0)	0.015
Kurtosis (excess)	1.189	Signif Level (Ku=0)	0.211
Jarque-Bera	8.469	Signif Level (JB=0)	0.014

Statistics on Series	France		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	1.402	Variance	2.460
Standard Error	1.568	of Sample Mean	0.273
t-Statistic (Mean=0)	5.135	Signif Level	0.000
Skewness	-0.955	Signif Level (Sk=0)	0.033
Kurtosis (excess)	2.050	Signif Level (Ku=0)	0.031
Jarque-Bera	10.798	Signif Level (JB=0)	0.005

Statistics on Series	Sweden		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	1.631	Variance	6.145
Standard Error	2.479	of Sample Mean	0.432
t-Statistic (Mean=0)	3.779	Signif Level	0.001
Skewness	-0.998	Signif Level (Sk=0)	0.026
Kurtosis (excess)	0.748	Signif Level (Ku=0)	0.431
Jarque-Bera	6.244	Signif Level (JB=0)	0.044

Statistics on Series	Gabon		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-1.231	Variance	52.492
Standard Error	7.245	of Sample Mean	1.261
t-Statistic (Mean=0)	-0.976	Signif Level	0.336
Skewness	-1.456	Signif Level (Sk=0)	0.001
Kurtosis (excess)	3.553	Signif Level (Ku=0)	0.000
Jarque-Bera	29.014	Signif Level (JB=0)	0.000

Statistics on Series	Swaziland		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	1.159	Variance	32.629
Standard Error	5.712	of Sample Mean	0.994
t-Statistic (Mean=0)	1.166	Signif Level	0.252
Skewness	0.688	Signif Level (Sk=0)	0.123
Kurtosis (excess)	0.898	Signif Level (Ku=0)	0.345
Jarque-Bera	3.713	Signif Level (JB=0)	0.156

Table H1 Continue

Statistics on Series	United Kingdom		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	2.376	Variance	6.116
Standard Error	2.473	of Sample Mean	0.431
t-Statistic (Mean=0)	5.520	Signif Level	0.000
Skewness	-1.171	Signif Level (Sk=0)	0.009
Kurtosis (excess)	1.966	Signif Level (Ku=0)	0.039
Jarque-Bera	12.851	Signif Level (JB=0)	0.002

Statistics on Series	Germany		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	1.658	Variance	4.208
Standard Error	2.051	of Sample Mean	0.357
t-Statistic (Mean=0)	4.644	Signif Level	0.000
Skewness	-1.291	Signif Level (Sk=0)	0.004
Kurtosis (excess)	3.071	Signif Level (Ku=0)	0.001
Jarque-Bera	22.130	Signif Level (JB=0)	0.000

Statistics on Series	Greece		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	1.443	Variance	8.560
Standard Error	2.926	of Sample Mean	0.509
t-Statistic (Mean=0)	2.834	Signif Level	0.008
Skewness	-0.307	Signif Level (Sk=0)	0.492
Kurtosis (excess)	-0.648	Signif Level (Ku=0)	0.496
Jarque-Bera	1.096	Signif Level (JB=0)	0.578

Statistics on Series	Grenada		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	3.753	Variance	42.397
Standard Error	6.511	of Sample Mean	1.133
t-Statistic (Mean=0)	3.311	Signif Level	0.002
Skewness	1.032	Signif Level (Sk=0)	0.021
Kurtosis (excess)	3.631	Signif Level (Ku=0)	0.000
Jarque-Bera	23.987	Signif Level (JB=0)	0.000

Statistics on Series	Guatemala		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	0.531	Variance	4.809
Standard Error	2.193	of Sample Mean	0.382
t-Statistic (Mean=0)	1.392	Signif Level	0.173
Skewness	-0.679	Signif Level (Sk=0)	0.129
Kurtosis (excess)	-0.004	Signif Level (Ku=0)	0.997
Jarque-Bera	2.533	Signif Level (JB=0)	0.282

Statistics on Series	Honduras		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	0.584	Variance	13.252
Standard Error	3.640	of Sample Mean	0.634
t-Statistic (Mean=0)	0.922	Signif Level	0.363
Skewness	-0.524	Signif Level (Sk=0)	0.240
Kurtosis (excess)	-0.492	Signif Level (Ku=0)	0.605
Jarque-Bera	1.846	Signif Level (JB=0)	0.397

Statistics on Series	Syria		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	1.426	Variance	34.628
Standard Error	5.885	of Sample Mean	1.024
t-Statistic (Mean=0)	1.392	Signif Level	0.174
Skewness	-1.042	Signif Level (Sk=0)	0.020
Kurtosis (excess)	2.392	Signif Level (Ku=0)	0.012
Jarque-Bera	13.845	Signif Level (JB=0)	0.001

Statistics on Series	Thailand		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	4.187	Variance	19.971
Standard Error	4.469	of Sample Mean	0.778
t-Statistic (Mean=0)	5.382	Signif Level	0.000
Skewness	-1.328	Signif Level (Sk=0)	0.003
Kurtosis (excess)	4.235	Signif Level (Ku=0)	0.000
Jarque-Bera	34.358	Signif Level (JB=0)	0.000

Statistics on Series	Tunisia		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	1.861	Variance	7.101
Standard Error	2.665	of Sample Mean	0.464
t-Statistic (Mean=0)	4.011	Signif Level	0.000
Skewness	-0.563	Signif Level (Sk=0)	0.208
Kurtosis (excess)	1.040	Signif Level (Ku=0)	0.274
Jarque-Bera	3.228	Signif Level (JB=0)	0.199

Statistics on Series	Turkey		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	1.966	Variance	19.620
Standard Error	4.429	of Sample Mean	0.771
t-Statistic (Mean=0)	2.550	Signif Level	0.016
Skewness	-0.483	Signif Level (Sk=0)	0.280
Kurtosis (excess)	-0.502	Signif Level (Ku=0)	0.598
Jarque-Bera	1.629	Signif Level (JB=0)	0.443

Statistics on Series	Uruguay		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	2.334	Variance	37.675
Standard Error	6.138	of Sample Mean	1.068
t-Statistic (Mean=0)	2.184	Signif Level	0.036
Skewness	-0.687	Signif Level (Sk=0)	0.124
Kurtosis (excess)	0.071	Signif Level (Ku=0)	0.940
Jarque-Bera	2.603	Signif Level (JB=0)	0.272

Statistics on Series	United Sattes		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	1.689	Variance	5.489
Standard Error	2.343	of Sample Mean	0.408
t-Statistic (Mean=0)	4.141	Signif Level	0.000
Skewness	-1.022	Signif Level (Sk=0)	0.022
Kurtosis (excess)	1.897	Signif Level (Ku=0)	0.046
Jarque-Bera	10.695	Signif Level (JB=0)	0.005

Table H1 Continue

Statistics on Series	Indonesia		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	3.460	Variance	14.782
Standard Error	3.845	of Sample Mean	0.669
t-Statistic (Mean=0)	5.170	Signif Level	0.000
Skewness	-3.358	Signif Level (Sk=0)	0.000
Kurtosis (excess)	14.621	Signif Level (Ku=0)	0.000
Jarque-Bera	355.954	Signif Level (JB=0)	0.000

Statistics on Series	India		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	3.958	Variance	10.395
Standard Error	3.224	of Sample Mean	0.561
t-Statistic (Mean=0)	7.052	Signif Level	0.000
Skewness	-0.234	Signif Level (Sk=0)	0.600
Kurtosis (excess)	0.092	Signif Level (Ku=0)	0.923
Jarque-Bera	0.314	Signif Level (JB=0)	0.855

Statistics on Series	Ireland		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	3.018	Variance	22.850
Standard Error	4.780	of Sample Mean	0.832
t-Statistic (Mean=0)	3.627	Signif Level	0.001
Skewness	-0.581	Signif Level (Sk=0)	0.193
Kurtosis (excess)	0.767	Signif Level (Ku=0)	0.420
Jarque-Bera	2.668	Signif Level (JB=0)	0.263

Statistics on Series	St. Vincent & Granadine		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	3.767	Variance	13.652
Standard Error	3.695	of Sample Mean	0.643
t-Statistic (Mean=0)	5.858	Signif Level	0.000
Skewness	0.475	Signif Level (Sk=0)	0.288
Kurtosis (excess)	0.866	Signif Level (Ku=0)	0.362
Jarque-Bera	2.273	Signif Level (JB=0)	0.321

Statistics on Series	Venezuela		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-0.525	Variance	39.595
Standard Error	6.292	of Sample Mean	1.095
t-Statistic (Mean=0)	-0.479	Signif Level	0.635
Skewness	0.189	Signif Level (Sk=0)	0.672
Kurtosis (excess)	-0.138	Signif Level (Ku=0)	0.885
Jarque-Bera	0.223	Signif Level (JB=0)	0.895

Statistics on Series	South Africa		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	0.98011	Variance	9.15841
Standard Error	3.026286	of Sample Mean	0.526809
t-Statistic (Mean=0)	1.860467	Signif Level	0.072031
Skewness	-0.372531	Signif Level (Sk=0)	0.404368
Kurtosis (excess)	-0.263917	Signif Level (Ku=0)	0.781436
Jarque-Bera	0.859058	Signif Level (JB=0)	0.650816

Table H2 Descriptive statistics of credit growth rate (%) data for each country

Statistics on Series	Argentina		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-244.637	Variance	403.141
Standard Error	635.478	of Sample Mean	110.623
t-Statistic (Mean=0)	-2.211	Signif Level	0.034
Skewness	-3.650	Signif Level (Sk=0)	0.000
Kurtosis (excess)	13.668	Signif Level (Ku=o)	0.000
Jarque-Bera	330.159	Signif Level (JB=0)	0.000

Statistics on Series	Antigua		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	5.850	Variance	45.942
Standard Error	6.778	of Sample Mean	1.180
t-Statistic (Mean=0)	4.958	Signif Level	0.000
Skewness	0.360	Signif Level (Sk=0)	0.420
Kurtosis (excess)	1.071	Signif Level (Ku=0)	0.260
Jarque-Bera	2.291	Signif Level (JB=0)	0.318

Statistics on Series	Australia		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	7.332	Variance	196.575
Standard Error	14.021	of Sample Mean	2.441
t-Statistic (Mean=0)	3.004	Signif Level	0.005
Skewness	0.772	Signif Level (Sk=0)	0.084
Kurtosis (excess)	1.052	Signif Level (Ku=0)	0.269
Jarque-Bera	4.800	Signif Level (JB=0)	0.091

Statistics on Series	Austria		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	6.005	Variance	182.173
Standard Error	13.497	of Sample Mean	2.350
t-Statistic (Mean=0)	2.556	Signif Level	0.016
Skewness	0.842	Signif Level (Sk=0)	0.060
Kurtosis (excess)	0.678	Signif Level (Ku=0)	0.476
Jarque-Bera	4.529	Signif Level (JB=0)	0.104

Statistics on Series	Burundi		
Annual Data From 197 8:01 To 2010:01			
Observations	33.000		
Sample Mean	2.330	Variance	137.891
Standard Error	37.053	of Sample Mean	6.450
t-Statistic (Mean=0)	0.361	Signif Level	0.720
Skewness	3.267	Signif Level (Sk=0)	0.000
Kurtosis (excess)	14.177	Signif Level (Ku=0)	0.000
Jarque-Bera	335.088	Signif Level (JB=0)	0.000

Statistics on Series	Belgium		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	6.937	Variance	697.327
Standard Error	26.407	of Sample Mean	4.597
t-Statistic (Mean=0)	1.509	Signif Level	0.141
Skewness	3.315	Signif Level (Sk=0)	0.000
Kurtosis (excess)	14.855	Signif Level (Ku=0)	0.000
Jarque-Bera	363.862	Signif Level (JB=0)	0.000

Statistics on Series	Iran		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-12.406	Variance	509.774
Standard Error	22.578	of Sample Mean	3.930
t-Statistic (Mean=0)	-3.156	Signif Level	0.003
Skewness	-0.136	Signif Level (Sk=0)	0.761
Kurtosis (excess)	-0.591	Signif Level (Ku=0)	0.534
Jarque-Bera	0.582	Signif Level (JB=0)	0.747

Statistics on Series	Iceland		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-3.861	Variance	112.179
Standard Error	33.544	of Sample Mean	5.839
t-Statistic (Mean=0)	-0.661	Signif Level	0.513
Skewness	0.100	Signif Level (Sk=0)	0.823
Kurtosis (excess)	0.563	Signif Level (Ku=0)	0.554
Jarque-Bera	0.491	Signif Level (JB=0)	0.782

Statistics on Series	Israel		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-38.472	Variance	731.371
Standard Error	85.512	of Sample Mean	14.886
t-Statistic (Mean=0)	-2.584	Signif Level	0.015
Skewness	-2.794	Signif Level (Sk=0)	0.000
Kurtosis (excess)	8.246	Signif Level (Ku=0)	0.000
Jarque-Bera	136.416	Signif Level (JB=0)	0.000

Statistics on Series	Italy		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	2.122	Variance	193.698
Standard Error	13.918	of Sample Mean	2.423
t-Statistic (Mean=0)	0.876	Signif Level	0.388
Skewness	0.016	Signif Level (Sk=0)	0.971
Kurtosis (excess)	0.644	Signif Level (Ku=0)	0.499
Jarque-Bera	0.571	Signif Level (JB=0)	0.752

Statistics on Series	Jordania		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	7.116	Variance	341.703
Standard Error	18.485	of Sample Mean	3.218
t-Statistic (Mean=0)	2.211	Signif Level	0.034
Skewness	0.229	Signif Level (Sk=0)	0.608
Kurtosis (excess)	6.519	Signif Level (Ku=0)	0.000
Jarque-Bera	58.715	Signif Level (JB=0)	0.000

Statistics on Series	Japan		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	8.928	Variance	195.544
Standard Error	13.984	of Sample Mean	2.434
t-Statistic (Mean=0)	3.668	Signif Level	0.001
Skewness	1.117	Signif Level (Sk=0)	0.012
Kurtosis (excess)	2.474	Signif Level (Ku=0)	0.009
Jarque-Bera	15.272	Signif Level (JB=0)	0.000

Table H2 Continue

Statistics on Series	Benin		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	6.692	Variance	122.807
Standard Error	34.997	of Sample Mean	6.092
t-Statistic (Mean=0)	1.099	Signif Level	0.280
Skewness	1.027	Signif Level (Sk=0)	0.022
Kurtosis (excess)	2.015	Signif Level (Ku=0)	0.034
Jarque-Bera	11.383	Signif Level (JB=0)	0.003

Statistics on Series	Burkina Faso		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	5.516	Variance	639.205
Standard Error	25.283	of Sample Mean	4.401
t-Statistic (Mean=0)	1.253	Signif Level	0.219
Skewness	0.896	Signif Level (Sk=0)	0.045
Kurtosis (excess)	2.518	Signif Level (Ku=0)	0.008
Jarque-Bera	13.128	Signif Level (JB=0)	0.001

Statistics on Series	Bangladesh		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	5.241	Variance	122.707
Standard Error	11.077	of Sample Mean	1.928
t-Statistic (Mean=0)	2.718	Signif Level	0.011
Skewness	0.734	Signif Level (Sk=0)	0.100
Kurtosis (excess)	2.853	Signif Level (Ku=0)	0.003
Jarque-Bera	14.156	Signif Level (JB=0)	0.001

Statistics on Series	Bahrain		
Annual Data From 197 8:01 To 2010:01			
Observations	30	Skipped/Missing	3
Sample Mean	-40.546	Variance	662.430
Standard Error	257.403	of Sample Mean	46.995
t-Statistic (Mean=0)	-0.863	Signif Level	0.395
Skewness	-4.028	Signif Level (Sk=0)	0.000
Kurtosis (excess)	18.542	Signif Level (Ku=0)	0.000
Jarque-Bera	510.887	Signif Level (JB=0)	0.000

Statistics on Series	Bahamas		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	4.663	Variance	49.327
Standard Error	7.023	of Sample Mean	1.223
t-Statistic (Mean=0)	3.814	Signif Level	0.001
Skewness	-2.218	Signif Level (Sk=0)	0.000
Kurtosis (excess)	8.158	Signif Level (Ku=0)	0.000
Jarque-Bera	118.556	Signif Level (JB=0)	0.000

Statistics on Series	Belize		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	9.028	Variance	153.633
Standard Error	12.395	of Sample Mean	2.158
t-Statistic (Mean=0)	4.184	Signif Level	0.000
Skewness	0.685	Signif Level (Sk=0)	0.125
Kurtosis (excess)	0.483	Signif Level (Ku=0)	0.612
Jarque-Bera	2.904	Signif Level (JB=0)	0.234

Statistics on Series	Kenia		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-0.849	Variance	377.002
Standard Error	19.417	of Sample Mean	3.380
t-Statistic (Mean=0)	-0.251	Signif Level	0.803
Skewness	-1.076	Signif Level (Sk=0)	0.016
Kurtosis (excess)	3.337	Signif Level (Ku=0)	0.000
Jarque-Bera	21.684	Signif Level (JB=0)	0.000

Statistics on Series	Korea Rep		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	8.221	Variance	173.988
Standard Error	13.190	of Sample Mean	2.296
t-Statistic (Mean=0)	3.580	Signif Level	0.001
Skewness	-0.451	Signif Level (Sk=0)	0.313
Kurtosis (excess)	1.523	Signif Level (Ku=0)	0.109
Jarque-Bera	4.308	Signif Level (JB=0)	0.116

Statistics on Series	Sri Lanka		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-0.436	Variance	405.980
Standard Error	20.149	of Sample Mean	3.507
t-Statistic (Mean=0)	-0.124	Signif Level	0.902
Skewness	0.492	Signif Level (Sk=0)	0.271
Kurtosis (excess)	0.932	Signif Level (Ku=0)	0.327
Jarque-Bera	2.524	Signif Level (JB=0)	0.283

Statistics on Series	Luxembourg		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	17.050	Variance	756.035
Standard Error	27.496	of Sample Mean	4.786
t-Statistic (Mean=0)	3.562	Signif Level	0.001
Skewness	1.750	Signif Level (Sk=0)	0.000
Kurtosis (excess)	6.226	Signif Level (Ku=0)	0.000
Jarque-Bera	70.146	Signif Level (JB=0)	0.000

Statistics on Series	Morocco		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	5.772	Variance	162.627
Standard Error	12.753	of Sample Mean	2.220
t-Statistic (Mean=0)	2.600	Signif Level	0.014
Skewness	0.026	Signif Level (Sk=0)	0.953
Kurtosis (excess)	0.096	Signif Level (Ku=0)	0.920
Jarque-Bera	0.016	Signif Level (JB=0)	0.992

Statistics on Series	Madagascar		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-10.241	Variance	882.262
Standard Error	29.703	of Sample Mean	5.171
t-Statistic (Mean=0)	-1.981	Signif Level	0.056
Skewness	0.014	Signif Level (Sk=0)	0.976
Kurtosis (excess)	-0.075	Signif Level (Ku=0)	0.937
Jarque-Bera	0.009	Signif Level (JB=0)	0.996

Table H2 Continue

Statistics on Series	Brazil		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-407.023	Variance	550.560
Standard Error	742.254	of Sample Mean	129.210
t-Statistic (Mean=0)	-3.150	Signif Level	0.004
Skewness	-2.201	Signif Level (Sk=0)	0.000
Kurtosis (excess)	4.301	Signif Level (Ku=0)	0.000
Jarque-Bera	52.071	Signif Level (JB=0)	0.000

Statistics on Series	Barbados		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	5.023	Variance	33.546
Standard Error	5.792	of Sample Mean	1.008
t-Statistic (Mean=0)	4.982	Signif Level	0.000
Skewness	0.181	Signif Level (Sk=0)	0.686
Kurtosis (excess)	-0.269	Signif Level (Ku=0)	0.777
Jarque-Bera	0.279	Signif Level (JB=0)	0.870

Statistics on Series	Canada		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	6.406	Variance	229.114419
Standard Error	15.137	of Sample Mean	2.635
t-Statistic (Mean=0)	2.431	Signif Level	0.021
Skewness	2.875	Signif Level (Sk=0)	0.000
Kurtosis (excess)	14.015	Signif Level (Ku=0)	0.000
Jarque-Bera	315.544	Signif Level (JB=0)	0.000

Statistics on Series	Chile		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-3.421	Variance	396.415
Standard Error	19.910	of Sample Mean	3.466
t-Statistic (Mean=0)	-0.987	Signif Level	0.331
Skewness	-0.749	Signif Level (Sk=0)	0.094
Kurtosis (excess)	0.232	Signif Level (Ku=0)	0.807
Jarque-Bera	3.157	Signif Level (JB=0)	0.206

Statistics on Series	China		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	11.001	Variance	153.068
Standard Error	12.372	of Sample Mean	2.154
t-Statistic (Mean=0)	5.108	Signif Level	0.000
Skewness	0.374	Signif Level (Sk=0)	0.402
Kurtosis (excess)	2.348	Signif Level (Ku=0)	0.014
Jarque-Bera	8.351	Signif Level (JB=0)	0.015

Statistics on Series	Cameroon		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	0.409	Variance	476.986
Standard Error	21.840	of Sample Mean	3.802
t-Statistic (Mean=0)	0.108	Signif Level	0.915
Skewness	-0.185	Signif Level (Sk=0)	0.680
Kurtosis (excess)	0.029	Signif Level (Ku=0)	0.976
Jarque-Bera	0.188	Signif Level (JB=0)	0.910

Statistics on Series	Mexico		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-21.034	Variance	194.619
Standard Error	44.075	of Sample Mean	7.672
t-Statistic (Mean=0)	-2.741	Signif Level	0.010
Skewness	-1.504	Signif Level (Sk=0)	0.001
Kurtosis (excess)	1.392	Signif Level (Ku=0)	0.143
Jarque-Bera	15.100	Signif Level (JB=0)	0.001

Statistics on Series	Mali		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-0.519	Variance	593.557
Standard Error	24.363	of Sample Mean	4.241
t-Statistic (Mean=0)	-0.122	Signif Level	0.903
Skewness	-0.666	Signif Level (Sk=0)	0.136
Kurtosis (excess)	1.779	Signif Level (Ku=0)	0.061
Jarque-Bera	6.795	Signif Level (JB=0)	0.033

Statistics on Series	Mauritius		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	3.238	Variance	198.565
Standard Error	14.091	of Sample Mean	2.453
t-Statistic (Mean=0)	1.320	Signif Level	0.196
Skewness	0.939	Signif Level (Sk=0)	0.036
Kurtosis (excess)	3.467	Signif Level (Ku=0)	0.000
Jarque-Bera	21.375	Signif Level (JB=0)	0.000

Statistics on Series	Malaysia		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	9.734	Variance	384.111
Standard Error	19.599	of Sample Mean	3.412
t-Statistic (Mean=0)	2.853	Signif Level	0.008
Skewness	0.588	Signif Level (Sk=0)	0.188
Kurtosis (excess)	6.773	Signif Level (Ku=0)	0.000
Jarque-Bera	64.981	Signif Level (JB=0)	0.000

Statistics on Series	Nigeria		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-2.869	Variance	591.673
Standard Error	76.907	of Sample Mean	13.388
t-Statistic (Mean=0)	-0.214	Signif Level	0.832
Skewness	3.474	Signif Level (Sk=0)	0.000
Kurtosis (excess)	16.429	Signif Level (Ku=0)	0.000
Jarque-Bera	437.529	Signif Level (JB=0)	0.000

Statistics on Series	Netherlands		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	5.745	Variance	190.805
Standard Error	13.813	of Sample Mean	2.405
t-Statistic (Mean=0)	2.389	Signif Level	0.023
Skewness	0.132	Signif Level (Sk=0)	0.767
Kurtosis (excess)	-0.513	Signif Level (Ku=0)	0.589
Jarque-Bera	0.459	Signif Level (JB=0)	0.795

Table H2 Continue

Statistics on Series	Colombia		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-6.525	Variance	421.457
Standard Error	20.529	of Sample Mean	3.574
t-Statistic (Mean=0)	-1.826	Signif Level	0.077
Skewness	0.081	Signif Level (Sk=0)	0.857
Kurtosis (excess)	-0.619	Signif Level (Ku=0)	0.516
Jarque-Bera	0.562	Signif Level (JB=0)	0.755

Statistics on Series	Costa Rica		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-6.662	Variance	958.965
Standard Error	30.967	of Sample Mean	5.391
t-Statistic (Mean=0)	-1.236	Signif Level	0.226
Skewness	-1.837	Signif Level (Sk=0)	0.000
Kurtosis (excess)	5.064	Signif Level (Ku=0)	0.000
Jarque-Bera	53.829	Signif Level (JB=0)	0.000

Statistics on Series	Germany		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	5.651	Variance	152.499
Standard Error	12.349	of Sample Mean	2.150
t-Statistic (Mean=0)	2.629	Signif Level	0.013
Skewness	0.798	Signif Level (Sk=0)	0.074
Kurtosis (excess)	0.310	Signif Level (Ku=0)	0.744
Jarque-Bera	3.638	Signif Level (JB=0)	0.162

Statistics on Series	Dominica		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	3.795	Variance	123.486
Standard Error	11.112	of Sample Mean	1.934
t-Statistic (Mean=0)	1.962	Signif Level	0.059
Skewness	1.354	Signif Level (Sk=0)	0.002
Kurtosis (excess)	2.828	Signif Level (Ku=0)	0.003
Jarque-Bera	21.079	Signif Level (JB=0)	0.000

Statistics on Series	Denmark		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	8.953	Variance	628.458
Standard Error	25.069	of Sample Mean	4.364
t-Statistic (Mean=0)	2.052	Signif Level	0.048
Skewness	3.632	Signif Level (Sk=0)	0.000
Kurtosis (excess)	16.768	Signif Level (Ku=0)	0.000
Jarque-Bera	459.152	Signif Level (JB=0)	0.000

Statistics on Series	Dominican Rep		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-5.780	Variance	156.732
Standard Error	39.519	of Sample Mean	6.879
t-Statistic (Mean=0)	-0.840	Signif Level	0.407
Skewness	-1.762	Signif Level (Sk=0)	0.000
Kurtosis (excess)	3.019	Signif Level (Ku=0)	0.002
Jarque-Bera	29.621	Signif Level (JB=0)	0.000

Statistics on Series	Nepal		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	5.528	Variance	233.319
Standard Error	15.275	of Sample Mean	2.659
t-Statistic (Mean=0)	2.079	Signif Level	0.046
Skewness	0.394	Signif Level (Sk=0)	0.378
Kurtosis (excess)	2.789	Signif Level (Ku=0)	0.003
Jarque-Bera	11.551	Signif Level (JB=0)	0.003

Statistics on Series	New Zealand		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	9.460	Variance	858.270
Standard Error	29.296	of Sample Mean	5.100
t-Statistic (Mean=0)	1.855	Signif Level	0.073
Skewness	3.297	Signif Level (Sk=0)	0.000
Kurtosis (excess)	15.235	Signif Level (Ku=0)	0.000
Jarque-Bera	378.927	Signif Level (JB=0)	0.000

Statistics on Series	Oman		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	9.451	Variance	107.336
Standard Error	32.792	of Sample Mean	5.708
t-Statistic (Mean=0)	1.656	Signif Level	0.108
Skewness	0.489	Signif Level (Sk=0)	0.273
Kurtosis (excess)	2.956	Signif Level (Ku=0)	0.002
Jarque-Bera	13.332	Signif Level (JB=0)	0.001

Statistics on Series	Pakistan		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-1.010	Variance	153.960
Standard Error	12.408	of Sample Mean	2.160
t-Statistic (Mean=0)	-0.468	Signif Level	0.643
Skewness	-0.354	Signif Level (Sk=0)	0.428
Kurtosis (excess)	0.084	Signif Level (Ku=0)	0.930
Jarque-Bera	0.699	Signif Level (JB=0)	0.705

Statistics on Series	Panama		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	4.969	Variance	90.311
Standard Error	9.503	of Sample Mean	1.654
t-Statistic (Mean=0)	3.004	Signif Level	0.005
Skewness	-0.364	Signif Level (Sk=0)	0.416
Kurtosis (excess)	0.364	Signif Level (Ku=0)	0.702
Jarque-Bera	0.910	Signif Level (JB=0)	0.634

Statistics on Series	Philippines		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	0.855	Variance	925.644
Standard Error	30.424	of Sample Mean	5.296
t-Statistic (Mean=0)	0.161	Signif Level	0.873
Skewness	0.720	Signif Level (Sk=0)	0.107
Kurtosis (excess)	6.428	Signif Level (Ku=0)	0.000
Jarque-Bera	59.662	Signif Level (JB=0)	0.000

Table H2 Continue

Statistics on Series	Ecuador		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	7.404	Variance	117.883
Standard Error	34.291	of Sample Mean	5.969
t-Statistic (Mean=0)	1.240	Signif Level	0.224
Skewness	3.907	Signif Level (Sk=0)	0.000
Kurtosis (excess)	20.279	Signif Level (Ku=0)	0.000
Jarque-Bera	649.415	Signif Level (JB=0)	0.000

Statistics on Series	Egypt		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-1.201	Variance	191.384
Standard Error	13.834	of Sample Mean	2.408
t-Statistic (Mean=0)	-0.499	Signif Level	0.621
Skewness	-0.735	Signif Level (Sk=0)	0.100
Kurtosis (excess)	0.743	Signif Level (Ku=0)	0.435
Jarque-Bera	3.731	Signif Level (JB=0)	0.155

Statistics on Series	Spain		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	4.921	Variance	230.220
Standard Error	15.173	of Sample Mean	2.641
t-Statistic (Mean=0)	1.863	Signif Level	0.072
Skewness	-0.269	Signif Level (Sk=0)	0.548
Kurtosis (excess)	-0.214	Signif Level (Ku=0)	0.822
Jarque-Bera	0.460	Signif Level (JB=0)	0.795

Statistics on Series	Finlandia		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	6.032	Variance	219.085
Standard Error	14.802	of Sample Mean	2.577
t-Statistic (Mean=0)	2.341	Signif Level	0.026
Skewness	-0.173	Signif Level (Sk=0)	0.699
Kurtosis (excess)	-0.235	Signif Level (Ku=0)	0.805
Jarque-Bera	0.240	Signif Level (JB=0)	0.887

Statistics on Series	Fiji		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	7.034	Variance	436.955
Standard Error	20.903	of Sample Mean	3.639
t-Statistic (Mean=0)	1.933	Signif Level	0.062
Skewness	1.211	Signif Level (Sk=0)	0.007
Kurtosis (excess)	5.095	Signif Level (Ku=0)	0.000
Jarque-Bera	43.763	Signif Level (JB=0)	0.000

Statistics on Series	France		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	10.058	Variance	219.715
Standard Error	46.816	of Sample Mean	8.150
t-Statistic (Mean=0)	1.234	Signif Level	0.226
Skewness	4.887	Signif Level (Sk=0)	0.000
Kurtosis (excess)	26.364	Signif Level (Ku=0)	0.000
Jarque-Bera	1087.024	Signif Level (JB=0)	0.000

Statistics on Series	Portugal		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	1.503	Variance	207.677
Standard Error	14.411	of Sample Mean	2.509
t-Statistic (Mean=0)	0.599	Signif Level	0.553
Skewness	-0.858	Signif Level (Sk=0)	0.055
Kurtosis (excess)	-0.102	Signif Level (Ku=0)	0.915
Jarque-Bera	4.065	Signif Level (JB=0)	0.131

Statistics on Series	Paraguay		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-3.930	Variance	826.022
Standard Error	28.741	of Sample Mean	5.003
t-Statistic (Mean=0)	-0.786	Signif Level	0.438
Skewness	0.164	Signif Level (Sk=0)	0.713
Kurtosis (excess)	0.348	Signif Level (Ku=0)	0.715
Jarque-Bera	0.314	Signif Level (JB=0)	0.854

Statistics on Series	Singapore		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	14.210	Variance	370.828
Standard Error	19.257	of Sample Mean	3.352
t-Statistic (Mean=0)	4.239	Signif Level	0.000
Skewness	1.679	Signif Level (Sk=0)	0.000
Kurtosis (excess)	5.318	Signif Level (Ku=0)	0.000
Jarque-Bera	54.396	Signif Level (JB=0)	0.000

Statistics on Series	El Salvador		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	4.405	Variance	212.567
Standard Error	14.580	of Sample Mean	2.538
t-Statistic (Mean=0)	1.736	Signif Level	0.092
Skewness	-1.502	Signif Level (Sk=0)	0.001
Kurtosis (excess)	3.994	Signif Level (Ku=0)	0.000
Jarque-Bera	34.340	Signif Level (JB=0)	0.000

Statistics on Series	Sweden		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	7.130	Variance	630.363
Standard Error	25.107	of Sample Mean	4.371
t-Statistic (Mean=0)	1.631	Signif Level	0.113
Skewness	1.103	Signif Level (Sk=0)	0.014
Kurtosis (excess)	5.683	Signif Level (Ku=0)	0.000
Jarque-Bera	51.092	Signif Level (JB=0)	0.000

Statistics on Series	Swaziland		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	12.460	Variance	608.457
Standard Error	77.990	of Sample Mean	13.576
t-Statistic (Mean=0)	0.918	Signif Level	0.366
Skewness	3.759	Signif Level (Sk=0)	0.000
Kurtosis (excess)	17.639	Signif Level (Ku=0)	0.000
Jarque-Bera	505.528	Signif Level (JB=0)	0.000

Table H2 Continue

Statistics on Series	Gabon		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	2.437	Variance	2591.398
Standard Error	50.906	of Sample Mean	8.862
t-Statistic (Mean=0)	0.275	Signif Level	0.785
Skewness	2.197	Signif Level (Sk=0)	0.000
Kurtosis (excess)	8.219	Signif Level (Ku=0)	0.000
Jarque-Bera	119.435	Signif Level (JB=0)	0.000

Statistics on Series	Syria		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-2.336	Variance	603.686
Standard Error	24.570	of Sample Mean	4.277
t-Statistic (Mean=0)	-0.546	Signif Level	0.589
Skewness	-1.021	Signif Level (Sk=0)	0.022
Kurtosis (excess)	0.395	Signif Level (Ku=0)	0.678
Jarque-Bera	5.943	Signif Level (JB=0)	0.051

Statistics on Series	United Kingdom		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	8.966	Variance	320.166
Standard Error	17.893	of Sample Mean	3.115
t-Statistic (Mean=0)	2.878	Signif Level	0.007
Skewness	3.018	Signif Level (Sk=0)	0.000
Kurtosis (excess)	13.195	Signif Level (Ku=0)	0.000
Jarque-Bera	289.476	Signif Level (JB=0)	0.000

Statistics on Series	Thailand		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	8.544	Variance	191.098
Standard Error	13.824	of Sample Mean	2.406
t-Statistic (Mean=0)	3.550	Signif Level	0.001
Skewness	-0.801	Signif Level (Sk=0)	0.073
Kurtosis (excess)	2.497	Signif Level (Ku=0)	0.009
Jarque-Bera	12.108	Signif Level (JB=0)	0.002

Statistics on Series	Greece		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	1.346	Variance	481.838
Standard Error	21.951	of Sample Mean	3.821
t-Statistic (Mean=0)	0.352	Signif Level	0.727
Skewness	2.460	Signif Level (Sk=0)	0.000
Kurtosis (excess)	9.996	Signif Level (Ku=0)	0.000
Jarque-Bera	170.663	Signif Level (JB=0)	0.000

Statistics on Series	Tunisia		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	2.040	Variance	107.671
Standard Error	10.376	of Sample Mean	1.806
t-Statistic (Mean=0)	1.129	Signif Level	0.267
Skewness	0.248	Signif Level (Sk=0)	0.579
Kurtosis (excess)	2.346	Signif Level (Ku=0)	0.014
Jarque-Bera	7.903	Signif Level (JB=0)	0.019

Statistics on Series	Grenada		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	5.830	Variance	92.011
Standard Error	9.592	of Sample Mean	1.670
t-Statistic (Mean=0)	3.491	Signif Level	0.001
Skewness	-0.238	Signif Level (Sk=0)	0.593
Kurtosis (excess)	0.732	Signif Level (Ku=0)	0.442
Jarque-Bera	1.049	Signif Level (JB=0)	0.592

Statistics on Series	Turkey		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-38.634	Variance	159.067
Standard Error	39.988	of Sample Mean	6.961
t-Statistic (Mean=0)	-5.550	Signif Level	0.000
Skewness	-0.548	Signif Level (Sk=0)	0.220
Kurtosis (excess)	0.598	Signif Level (Ku=0)	0.530
Jarque-Bera	2.145	Signif Level (JB=0)	0.342

Statistics on Series	Guatemala		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	0.221	Variance	475.014
Standard Error	21.795	of Sample Mean	3.794
t-Statistic (Mean=0)	0.058	Signif Level	0.954
Skewness	-2.342	Signif Level (Sk=0)	0.000
Kurtosis (excess)	7.464	Signif Level (Ku=0)	0.000
Jarque-Bera	106.787	Signif Level (JB=0)	0.000

Statistics on Series	Uruguay		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-27.372	Variance	202.319
Standard Error	45.026	of Sample Mean	7.838
t-Statistic (Mean=0)	-3.492	Signif Level	0.001
Skewness	0.136	Signif Level (Sk=0)	0.761
Kurtosis (excess)	0.096	Signif Level (Ku=0)	0.920
Jarque-Bera	0.114	Signif Level (JB=0)	0.944

Statistics on Series	Honduras		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-1.673	Variance	390.081
Standard Error	19.750	of Sample Mean	3.438
t-Statistic (Mean=0)	-0.487	Signif Level	0.630
Skewness	-0.388	Signif Level (Sk=0)	0.386
Kurtosis (excess)	1.202	Signif Level (Ku=0)	0.206
Jarque-Bera	2.812	Signif Level (JB=0)	0.245

Statistics on Series	United Sattes		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	5.139	Variance	20.929
Standard Error	4.575	of Sample Mean	0.796
t-Statistic (Mean=0)	6.453	Signif Level	0.000
Skewness	-0.817	Signif Level (Sk=0)	0.067
Kurtosis (excess)	1.305	Signif Level (Ku=0)	0.170
Jarque-Bera	6.015	Signif Level (JB=0)	0.049

Table H2 Continue

Statistics on Series	Indonesia		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	0.244	Variance	105.854
Standard Error	32.555	of Sample Mean	5.667
t-Statistic (Mean=0)	0.043	Signif Level	0.966
Skewness	-2.232	Signif Level (Sk=0)	0.000
Kurtosis (excess)	7.567	Signif Level (Ku=0)	0.000
Jarque-Bera	106.133	Signif Level (JB=0)	0.000

Statistics on Series	St. Vincent & Granadine		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	4.924	Variance	63.751
Standard Error	7.984	of Sample Mean	1.390
t-Statistic (Mean=0)	3.543	Signif Level	0.001
Skewness	-0.627	Signif Level (Sk=0)	0.160
Kurtosis (excess)	0.671	Signif Level (Ku=0)	0.480
Jarque-Bera	2.784	Signif Level (JB=0)	0.249

Statistics on Series	India		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	3.884	Variance	114.050
Standard Error	10.679	of Sample Mean	1.859
t-Statistic (Mean=0)	2.089	Signif Level	0.045
Skewness	-0.776	Signif Level (Sk=0)	0.083
Kurtosis (excess)	2.076	Signif Level (Ku=0)	0.029
Jarque-Bera	9.232	Signif Level (JB=0)	0.010

Statistics on Series	Venezuela		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-19.909	Variance	208.076
Standard Error	45.608	of Sample Mean	7.939
t-Statistic (Mean=0)	-2.508	Signif Level	0.017
Skewness	-1.441	Signif Level (Sk=0)	0.001
Kurtosis (excess)	3.273	Signif Level (Ku=0)	0.001
Jarque-Bera	26.148	Signif Level (JB=0)	0.000

Statistics on Series	Ireland		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	12.626	Variance	428.678
Standard Error	20.705	of Sample Mean	3.604
t-Statistic (Mean=0)	3.503	Signif Level	0.001
Skewness	0.804	Signif Level (Sk=0)	0.072
Kurtosis (excess)	2.056	Signif Level (Ku=0)	0.031
Jarque-Bera	9.374	Signif Level (JB=0)	0.009

Statistics on Series	South Africa		
Annual Data From 197 8:01 To 2010:01			
Observations	33		
Sample Mean	-2.111	Variance	267.803
Standard Error	16.365	of Sample Mean	2.849
t-Statistic (Mean=0)	-0.741	Signif Level	0.464
Skewness	0.795	Signif Level (Sk=0)	0.075
Kurtosis (excess)	1.999	Signif Level (Ku=0)	0.036
Jarque-Bera	8.971	Signif Level (JB=0)	0.011

Appendix I. Historical decomposition of GDP growth rate and credit growth rate

The Figure I.1 plots the historical fluctuations of GDP, the global component, the variable component and the idiosyncratic component (namely the country specific component and the residual term).

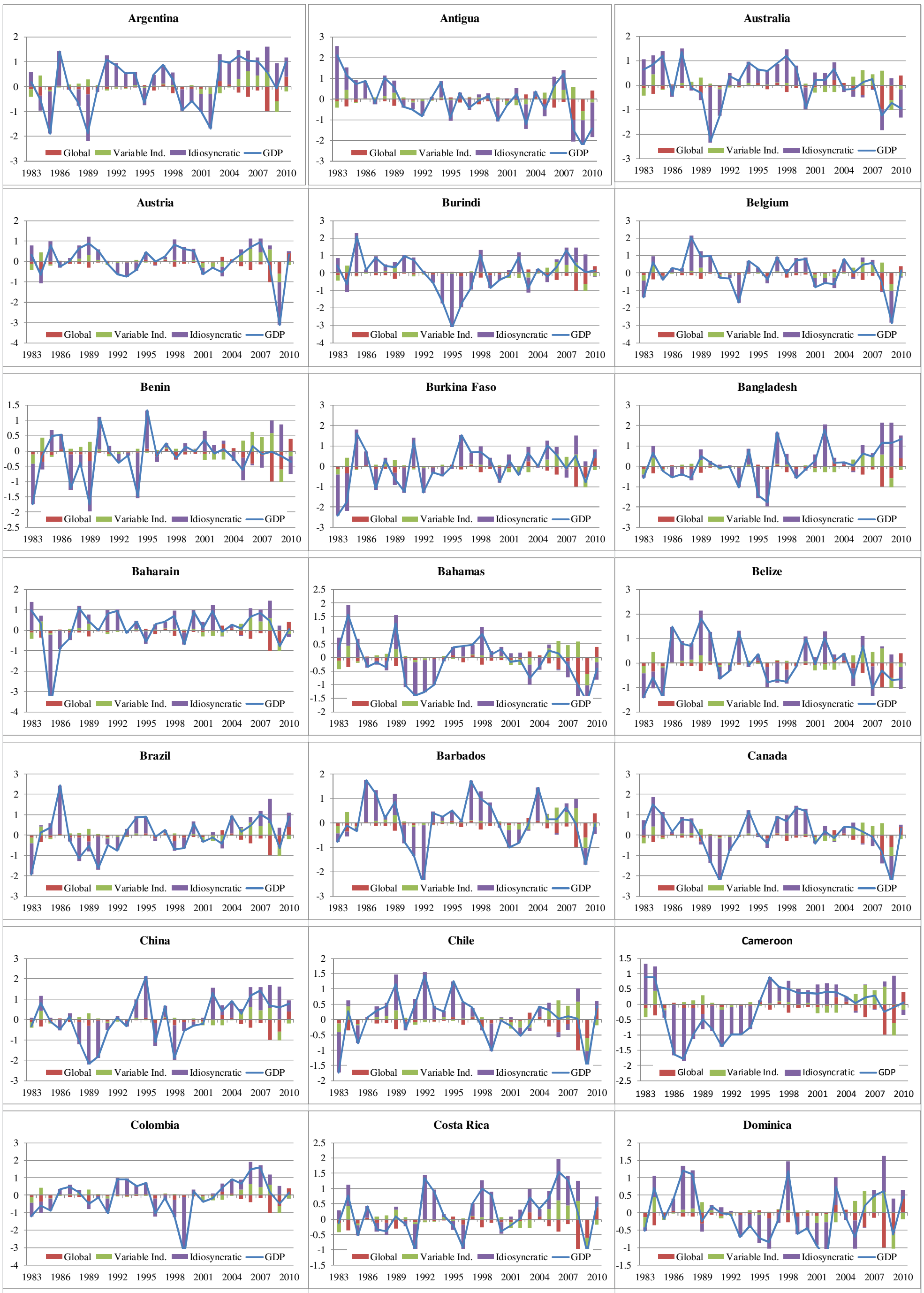


Fig. I1 Historical decomposition of fluctuations of GDP

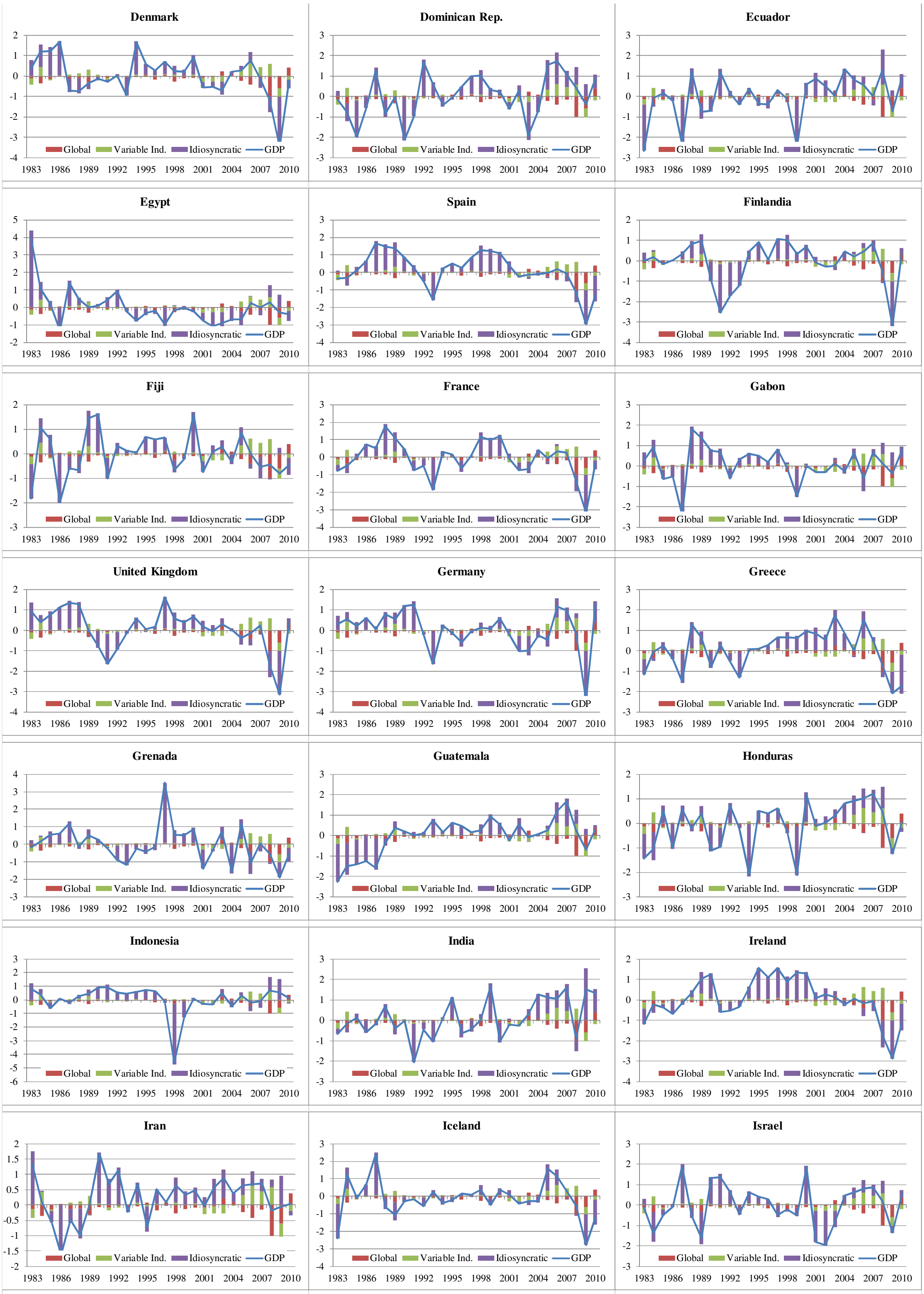
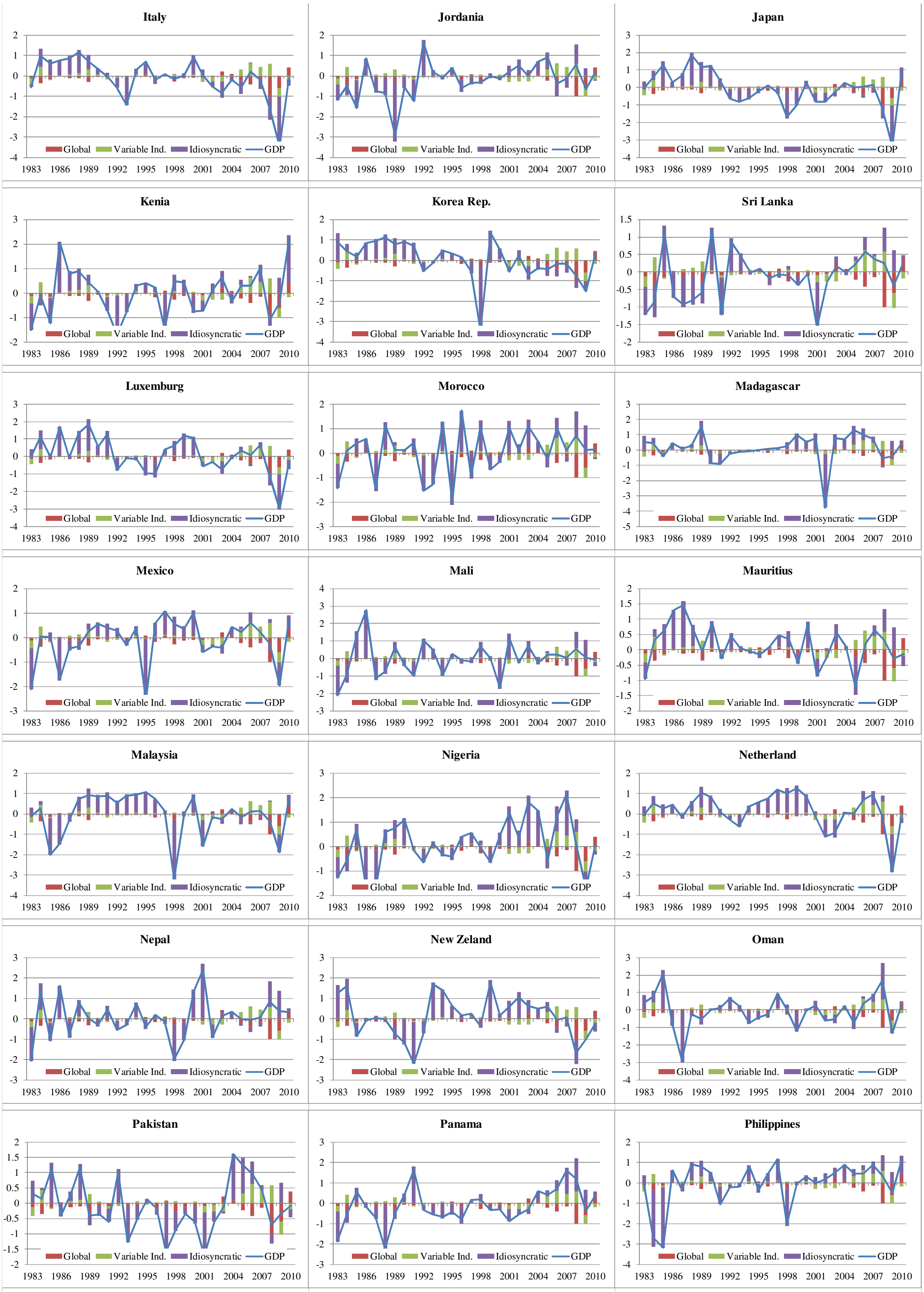


Fig. I1 Continue


Italy
Jordania
Japan
Kenia
Korea Rep.
Sri Lanka
Luxemburg
Morocco
Madagascar
Mexico
Mali
Mauritius
Malaysia
Nigeria
Netherland
Nepal
New Zeland
Oman
Pakistan
Panama
Philippines
Global
Variable Ind.
Idiosyncratic
GDP
1983 1986 1989 1992 1995 1998 2001 2004 2007 2010

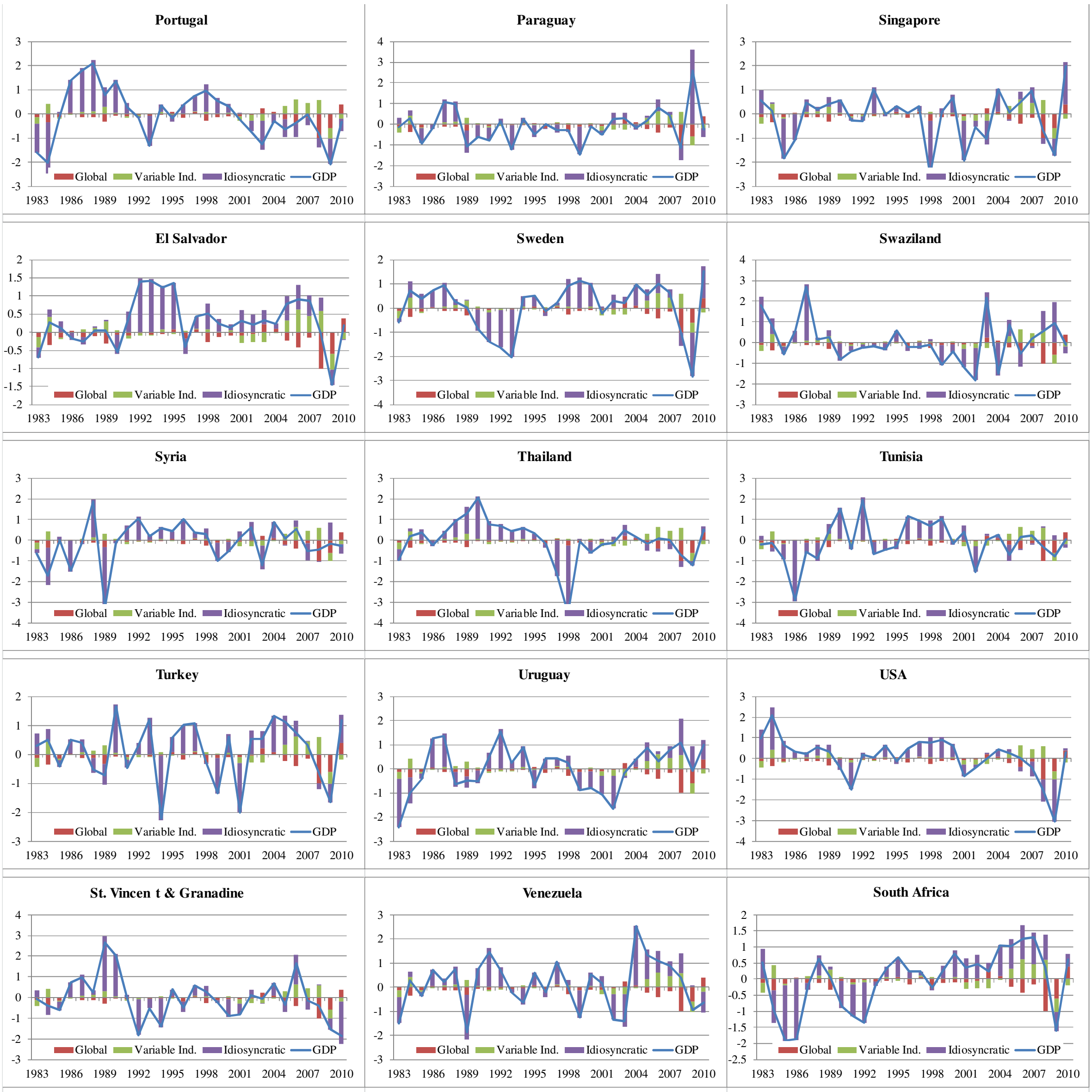


Fig. I1 Continue

The Figure I.2 plots the historical fluctuations of credit, the global component, the variable component and the idiosyncratic component.

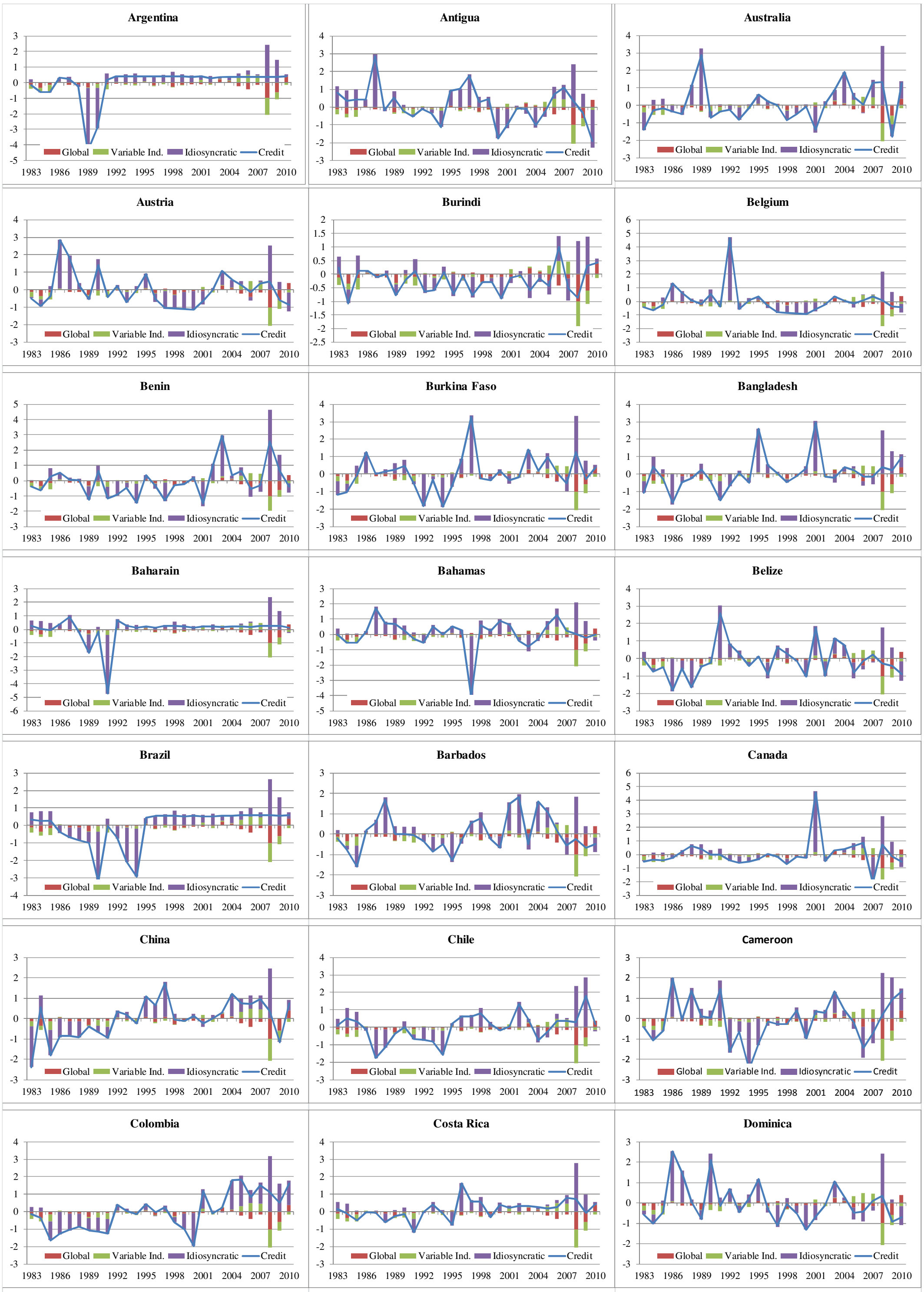


Fig. I2 Historical decomposition of fluctuations of the credit

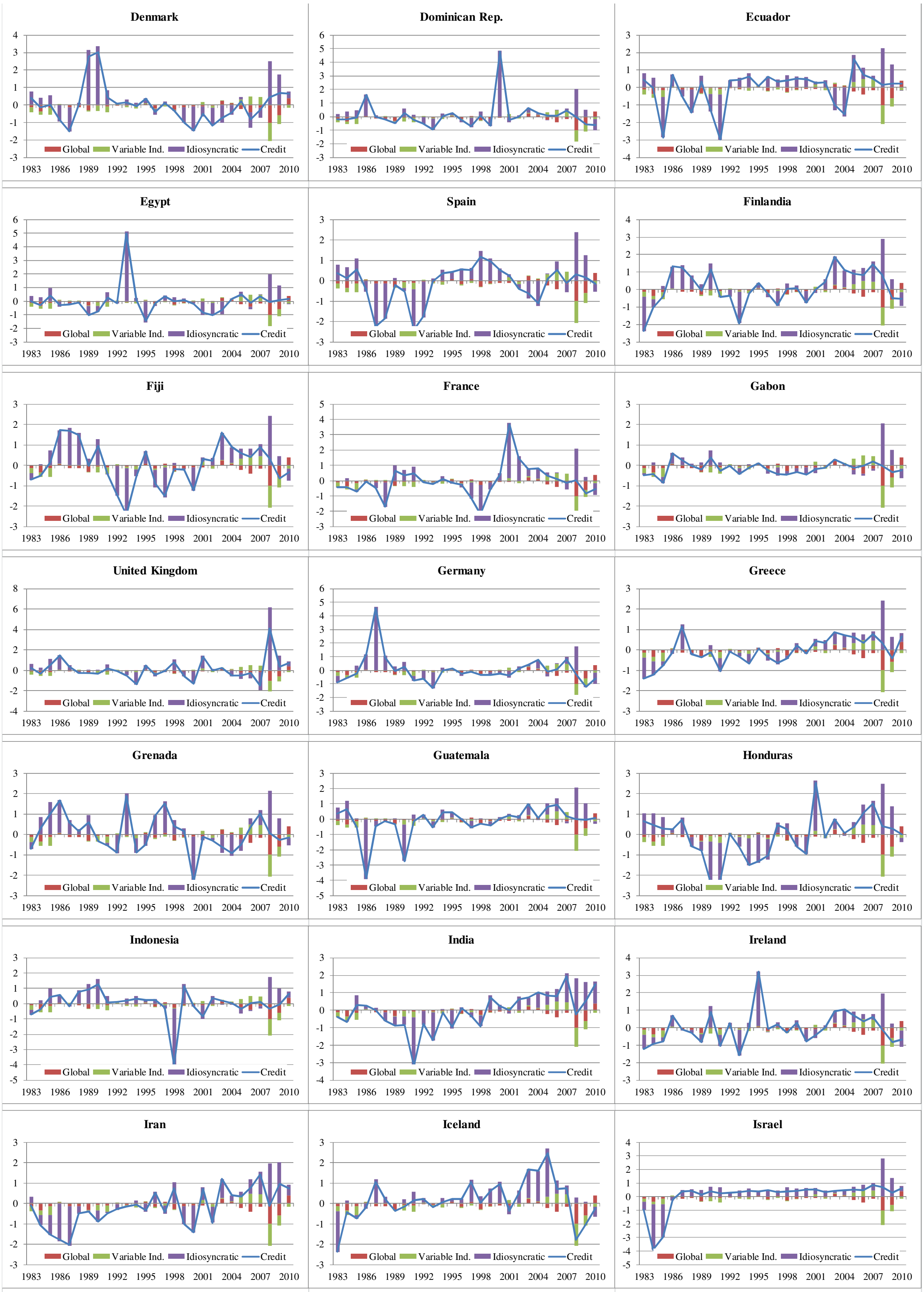


Fig. I2 Continue

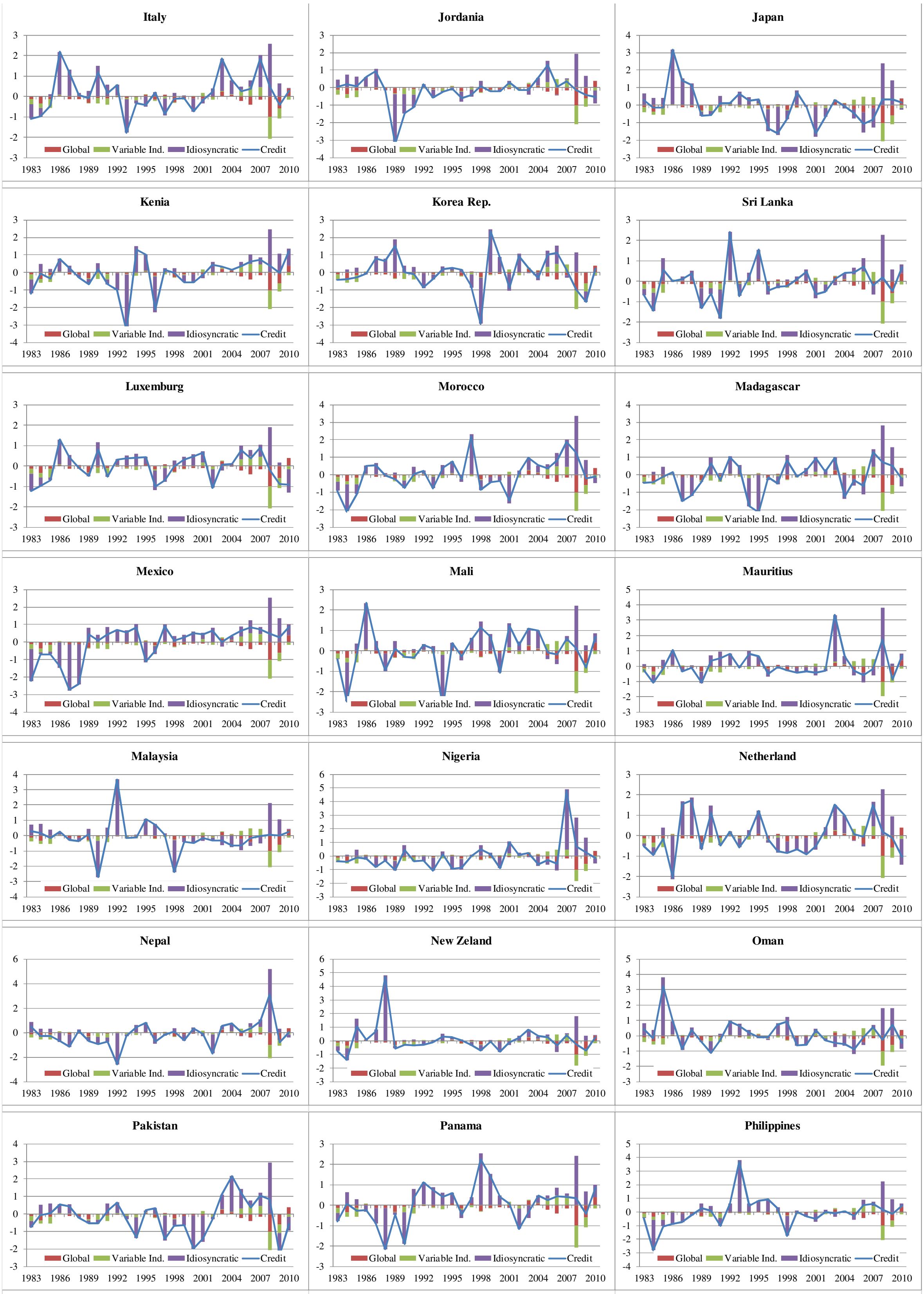


Fig. I2 Continue

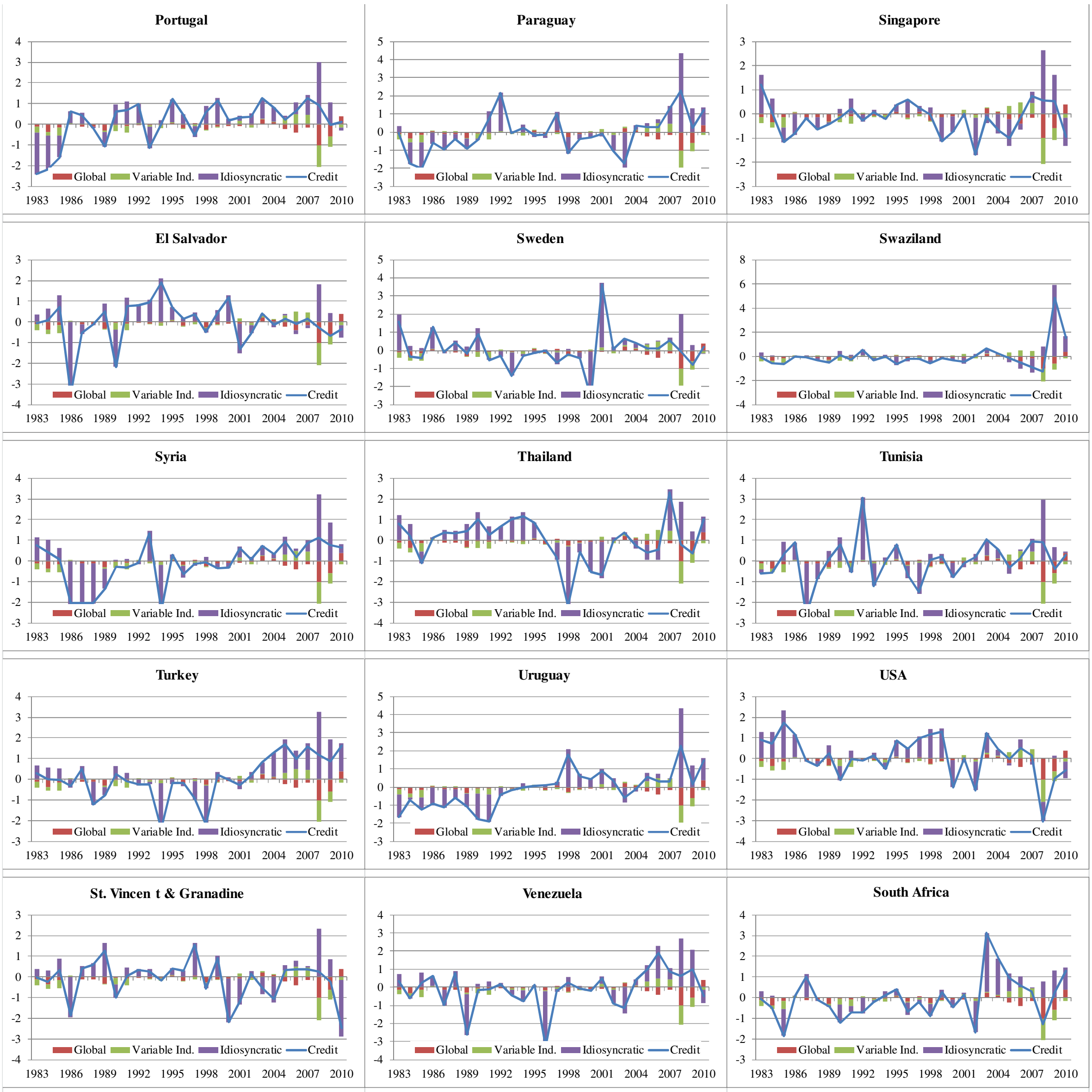


Fig. I2 Continue

Appendix J. Additional results

On the basis of the consideration did in the appendix F, this appendix presents the results of the CAs, for both credit and real shocks spreading from AEs, obtained using the model estimated on the entire data sample (1978-2010).

Spread of credit shocks from the AEs to the EEs

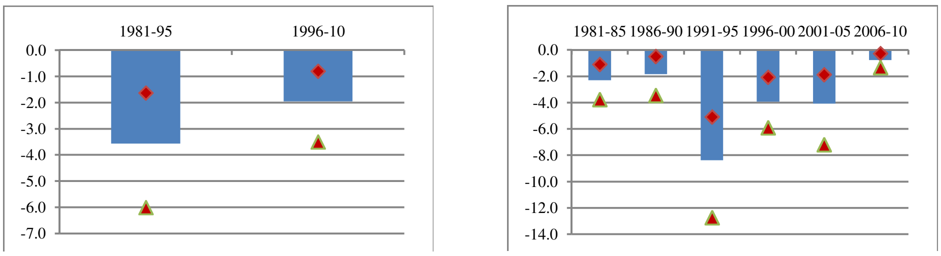
The median impact for the entire group of EEs, calculated at different sub-samples, is shown in Table J.1, together with the lower and the upper values (16th and the 84th percentiles, respectively).

Table J.1 Dynamic impact of the credit shock spreading from AEs to Emerging Economies; additional results

	t+1			*t+2*			*t+3*			*t+4*			cumulate impact		
	U	M	L	U	M	L	U	M	L	U	M	L	U	M	L
1981-1995	-0.188	-0.402	-0.629	0.028	-0.106	-0.247	-1.758	-2.996	-4.597	0.291	-0.067	-0.533	-1.627	-3.571	-6.005
1996-2010	-0.110	-0.324	-0.523	-0.015	-0.111	-0.205	-0.688	-1.339	-2.353	0.016	-0.178	-0.420	-0.797	-1.952	-3.501
Subsamples															
1983-1985	-0.213	-0.496	-0.757	-0.155	-0.259	-0.363	-0.687	-1.155	-1.881	-0.056	-0.394	-0.767	-1.112	-2.304	-3.768
1986-1990	-0.179	-0.353	-0.548	0.127	0.025	-0.078	-0.885	-1.550	-2.642	0.455	0.031	-0.177	-0.482	-1.847	-3.445
1991-1995	-0.187	-0.419	-0.666	0.036	-0.186	-0.414	-5.345	-7.688	-10.569	0.407	-0.084	-1.094	-5.089	-8.377	-12.742
1996-2000	-0.091	-0.312	-0.505	-0.006	-0.122	-0.235	-1.986	-3.093	-4.199	0.021	-0.407	-0.979	-2.063	-3.934	-5.919
2001-2005	-0.097	-0.324	-0.501	-0.031	-0.126	-0.224	-1.716	-3.258	-5.376	-0.038	-0.362	-1.100	-1.881	-4.071	-7.202
2006-2010	-0.133	-0.333	-0.565	-0.008	-0.089	-0.171	-0.166	-0.267	-0.428	0.030	-0.075	-0.171	-0.278	-0.764	-1.336

Note: M stands for median, L and U stand for lower and upper values (16^{th} and the 84^{th} percentiles, respectively).

The cumulated median responses, shown also graphically in Figure J.1, 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 fifteen years (Figure J.1, panel 1). The resilience of the EEs, as can be deduced from the cumulated impact, seems to have been particularly strong during the last five years of the sample period, that is from 2006 to 2010 (see Figure J.1, panel 2); in fact the EEs' resilience to external credit shocks



1. 2.

Fig. J.1 Cumulated (median, 16^{th} and 84^{th} percentiles) impact of the credit shock spreading from AEs to EEs; additional results reached its nadir in the early 1990s, thereafter it improved, but it was only in the period 2006-2010 that the cumulated median impact was lower (about 58%) than it had been during the period 1983-1985.

Spread of real shocks from the AEs to the EEs

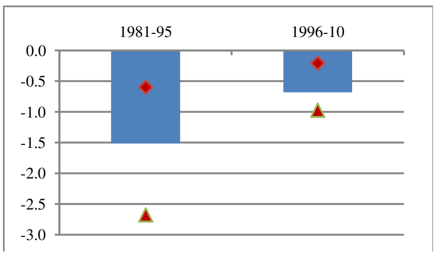
Table J.2 shows the median impact for the entire group of EEs. The analysis of the results reveals that the force of the impact of the simulated AEs' real shock on the EEs over the last fifteen years was lower than that recorded during the previous fifteen

Table J.2 Dynamic impact of the real shock spreading from AEs to Emerging Economies; additional results

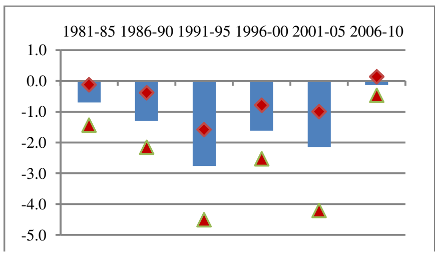
	t+1			*t+2*			*t+3*			*t+4*			cumulated impact		
	U	M	L	U	M	L	U	M	L	U	M	L	U	M	L
1983-1995	-0.012	-0.168	-0.312	0.017	-0.057	-0.132	-0.766	-1.262	-1.919	0.168	-0.025	-0.308	-0.593	-1.512	-2.671
1996-2010	0.017	-0.116	-0.242	-0.006	-0.063	-0.242	-0.247	-0.416	-0.242	0.033	-0.085	-0.242	-0.203	-0.679	-0.968
Subsamples															
1983-1985	0.000	-0.152	-0.292	0.010	-0.056	-0.118	-0.235	-0.390	-0.684	0.105	-0.100	-0.334	-0.120	-0.697	-1.427
1986-1990	-0.073	-0.212	-0.337	0.051	-0.018	-0.089	-0.587	-1.062	-1.592	0.226	0.004	-0.125	-0.382	-1.286	-2.144
1991-1995	0.034	-0.123	-0.295	-0.021	-0.107	-0.191	-1.755	-2.477	-3.455	0.163	-0.048	-0.556	-1.579	-2.754	-4.497
1996-2000	0.012	-0.112	-0.234	-0.032	-0.091	-0.148	-0.781	-1.246	-1.728	0.014	-0.158	-0.418	-0.787	-1.607	-2.527
2001-2005	-0.021	-0.152	-0.283	-0.020	-0.090	-0.161	-0.922	-1.684	-2.842	-0.034	-0.221	-0.914	-0.997	-2.147	-4.200
2006-2010	0.058	-0.078	-0.212	0.022	-0.024	-0.068	0.032	-0.038	-0.108	0.032	0.007	-0.075	0.143	-0.133	-0.463

Note: M stands for median, U and L stand for upper and lower values (16th and the 84th percentiles, respectively).

years (both in terms of immediate and cumulated impact). When the entire sample period was broken down into five-year sub-periods, as with the case of the credit shock, also in the case of real shock it emerges a rather interesting result. 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 cumulated impact of the simulated real external shock was 80% lower than it was in the five-year period 1981-1985.



1.



2.

Fig. J.2 Cumulated (median, 16th and 84th percentiles) impact of the real shock spreading from AE to EEs; additional results

5. Conclusions

In this monograph, I analysed the way in which the degree of vulnerability of EEs to shocks from AEs has changed over the past 30 years. I sought to contribute to the debate concerning the decoupling of EEs, namely the debate on the possibility that EEs may have become less dependent on the economic performance of advanced economies, i.e., the now long-discussed hypothesis that EEs are currently less vulnerable than in the past to possible adverse economic scenarios affecting AEs.

In recent decades, the importance of EEs in the international economic scenario has gradually increased. It is striking that, on the basis of global GDP share[90], the G7 (the group of the seven nations with the world's largest economies) would consist of the United States, China, India, Japan, Germany, Russia and Brazil, i.e., three advanced economies and four emerging economies, rather than its current official members (the United States, Japan, Germany, France, the United Kingdom, Italy and Canada), i.e. solely AEs. The economic importance of EEs at the global level has grown in various areas. The increases in their shares of global trade and international capital flows have been driven not only by technological innovation and economic policies in favour of international trade and financial exchange, resulting in increasing economic integration between EEs and AEs, but also by reinforcement of the economic ties between the various EEs.

If, on the one hand, it is plausible that the global economic scenario, characterized by an international network of economic relationships that has become increasingly dense and complex over time, has increased its capacity to serve as a channel for transmitting shocks from one country to another, on the other hand it is also possible to hold that the strengthening economic ties between EEs, along with the growth of their domestic markets, have made EEs less vulnerable to shocks from AEs.

The results of the empirical investigation proposed in this monograph suggest that EEs indeed have become less vulnerable to eventual adverse scenarios in AEs, without of course becoming immune to such events, but rather remaining sensitive to them, as also emphasized by the recent financial crisis.

While the synchronization of the economic cycles of advanced and emerging economies (measured by the correlation between GDP growth rates) does not show a

[90] In 2013, the shares of global GDP, at purchasing-power parity, of the United States, China, India, Japan, Germany, Russia and Brazil were 19.3%, 15.4%, 5.7%, 5.5%, 3.7%, 3.0% and 2.8%, respectively (source: International Monetary Fund, World Economic Outlook Database).

clear tendency to decrease and suggests that one could rule out the possibility that the ties between advanced and emerging economies have declined over time, a more thorough and in-depth analysis conducted using simulation experiments indicates that over the last thirty years EEs have become less vulnerable (albeit with particularities in the various geographical areas) to shocks from AEs, whether of a real or credit nature. Despite this evidence in favour of the decoupling hypothesis, it is important to note that EEs' resilience to external shocks has changed in a non-progressive manner over time, with phases of greater resilience followed by phases of lower resilience, and vice versa; this outlines a "wave-like" path whose evidence has yet been fully analyzed.

In terms of the nature of "external" shocks (namely shocks spreading from AEs), EEs are more sensitive to credit shocks than real ones, and this greater relative vulnerability intensified during the final years of the sample period used in this monograph.

In light of these results, below I discuss some policy implications, and then also indicate some possible extensions of the study presented in this monograph for future research on the subject of decoupling.

EEs may represent a valid opportunity for the diversification of risks by foreign investors. Accordingly, AEs have good reasons to reinforce real and financial channels with EEs. However, the reinforcement of financial ties, such as, for example, the credit channel, presents important challenges that must be managed through appropriate regulation.

EEs are more highly sensitive to credit shocks than real shocks. Consequently, the level and nature of the exposure of their financial systems to foreign banks must be carefully monitored. It is therefore necessary to define regulations for the credit channel that reduce the possibility that foreign banks may serve as the vehicle for financial contagion. Foreign bank credit for emerging economies may be provided in essentially two forms: direct credit disbursed by the foreign banks' headquarters (cross-border) or through affiliates operating in the host country. The two forms of foreign credit may act differently in a scenario of financial stress external to the country. As illustrated, for example, by Kamil and Rai (2010), following the 2008 default of the investment bank Lehman Brothers, the foreign bank credit disbursed to the Latin American and Caribbean region slowed rapidly; however, most of this slowdown was the consequence of the sharp decline in cross-border loans, which are primarily denominated in foreign currencies and funded through recourse to the interbank or bond market. On the other hand, the credit disbursed by the affiliates of foreign banks, primarily denominated in the local currency and funded through domestic deposits, continued to grow even at the height of the global turmoil. In regulating foreign banks' participation in their economies, politicians in EEs must somehow take account of the different strategies employed by multinational banks in their foreign credit activity (cross-border or through affiliates operating in the host country), as well as the sources of funding and financial autonomy granted to foreign affiliates operating in host countries.

The results of this work also highlight the importance of some policy implications for the global economy that have already been debated in the G20 and other international forums (see Kose and Prasad, 2010). Attention has been drawn to the importance of also involving countries with emerging economies in order to coordinate national policies and set international policies in response to regional and global shocks. It might also be helpful to strengthen the representation of emerging economies (at least the largest among them) within international financial institutions, in order to improve the stability of the international monetary system. In this regard, during the summit organized in 2013 in Durban, South Africa, the BRICS group (Brazil, Russia, India, China and South Africa) announced a desire to establish a BRICS Bank capable of competing with the International Monetary Fund in order to achieve greater relevance in the global economic scenario.

The study presented in this monograph may be extended in various directions. First of all, one might identify the various fundamental variables underlying the decoupling phenomenon, and more precisely estimate the relationships between such variables and decoupling. Such estimates could also explain why, although on the whole EEs are currently more resistant to shocks of an "external" nature (i.e., from outside the group of EEs) than in the early years of globalization, the process of reinforcement has not been linear, but rather characterized by phases of lesser vulnerability (greater resilience) followed by phases of greater vulnerability (lesser resilience), and vice versa.

It could also be interesting to focus attention on individual emerging countries as case studies in order to identify the relationship between the degree of resilience of a given country and the structural characteristics of its economy, not only at a macroscopic level, such as its level of openness to trade and financial dealings, but also at a more detailed level, such as the characteristics of its industrial system for example. It might be useful to study the role of the geographical proximity of the country, and in this way one could also study in-deph the regional peculiarities which also emerged in this research.

The case studies could also be interesting in order to compare, for example, a given country's degree of resilience with its specific political scenario or the implementation of country specific economic policies.

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