Dynamics of Global Business Cycles Interdependence*

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Abstract

In this paper, we provide a comprehensive analysis of the time-varying interdependence among the economic cycles of the major world economies during the post-Great Moderation period. We document a structural increase in the global business cycles interdependence occurred in the early 2000s. Such increase is mainly attributed to the emerging market economies, since their business cycles became more synchronized with the rest of the world around that time. Moreover, we find that the break in global interdependence can be explained by decreasing differences in sectoral composition among countries, specifically in the agricultural component.

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1 Introduction

Recent decades have witnessed increased globalization of the world economy associated with economic and financial integration among countries. On the one hand, economic and financial integration may exert a positive effect on economic growth by reducing transaction costs, ameliorating information asymmetries, facilitating specialization among countries according to their comparative advantage, and facilitating the transfer of resources across countries. On the other hand, economic and financial integration, which is associated with high business cycle interdependence, may increase global systemic risk, since country-specific shocks can be rapidly transmitted to other economies.

Moreover, the degree of economic interdependence of a given country with the rest of the world may experience significant changes over time due to several reasons, such as policy shocks, financial liberalization, economic unions, trade agreements, just to mention a few. Therefore, understanding the i) time-varying patterns and ii) underlying mechanisms governing world economic interdependence is crucial for policy makers and investors to evaluate the changing degree of exposure that a given country has to external shocks.

On the one hand, the patterns of global business cycles synchronization have been previously analyzed by looking at the variability of country-specific GDP growth explained by a "global component", identified with Dynamic Factor Models (DFM), see Kose et al. (2012), Kose et al. (2003), among others. However, a couple of aspects deserve some discussion. First, although DFM are helpful to assess the world (regional) economic influence on a country-specific economy, they provide no information on the bilateral synchronization, i.e. business cycles pairwise interlinkages, potentially driven by factors such as bilateral trade. Second, although one of the defining characteristics of the business cycle is its asymmetric nature, Burns and Mitchell (1946), these studies follow linear frameworks, potentially capturing common shocks rather than common cycles among countries. Since the degree and speed of the propagation of business cycle shocks may also depend on country-specific economic phases (recession or expansion), accounting for nonlinear dynamics is essential to analyze business cycles interdependence.

To analyze interdependence accounting for nonlinear dynamics, Harding and Pagan (2006) and Camacho et al. (2008) focus on assessing the synchronization between the cycles. Specifically, they test whether countries enter recessionary and expansionary phases simultaneously or independently. Although the frameworks used in these studies provide an overall assessment of the interdependence between the economic cycles of a set of countries, such assessment is "static", i.e. time-invariant. Therefore, to identify potential changes in the interdependence of cycles the sample has to be split on a given (exogenous) date, which might increase the risk of pretesting bias (Diebold, 2015).

On the other hand, to identify the underlying factors explaining the interdependence of business cycles most of the studies in the literature stream have used the correlation of GDP growth (or de-trended GDP) between pairs of countries as a measure of business cycle synchronization and relied on cross-section analysis to assess its main determinants. Previous studies find a positive relationship between business cycles synchronization and trade (Imbs (2004)), financial integration (Frankel and Rose (1998)), currency unions (Rose and Engel (2002)), sectoral composition, public sector size (Camacho et al. (2008)), institutional environment and cultural factors (Altug and Canova (2012)). These determinants may also vary across different sets of countries. Imbs (2006) and Clark and van Wincoop (2001) find high synchronization between financially open developing countries and the G7. Canova and Ciccarelli (2012) and Canova and Schlaepfer (2013) analyze business cycle interdependence among Mediterranean countries and find that traditional transmission channels, such as trade and financial integration, are not very important determinants of business cycle interdependence in this region.

Although these studies contribute to a better understanding of the factors influencing business cycle interdependence, they have two important limitations. First, none of these studies account for model uncertainty, which is motivated by the lack of consensus in the theoretical and empirical business cycle literature regarding the main factors driving business cycle co-movement. Instead, these studies only rely on small pre-determined sets of potential determinants and assess their corresponding statistical significance, potentially incurring in a problem of omitted variables, which may yield bias estimates. As suggested in Sala-i-Martin et al. (2004), a natural way to think about model uncertainty is to admit that we do not know which model is "true" and, instead, attach probabilities to different models. Second, these studies use time-invariant measures of synchronization and therefore, are not able to identify the sources of potential changes in global business cycles interdependence. Moreover, notice that if synchronization patterns and their potential determinants do experience significant variation over time, a cross-sectional regression analysis may yield misleading insights about the underlying factors driving business cycle interdependence.

This paper analyses the dynamics of global business cycles interdependence and assess their the main explanatory factors, accounting for the drawbacks above mentioned. Specifically, we consider the time-varying index of business cycle interdependence recently proposed by Leiva-Leon (2014). This index endogenously identifies changes in the synchronization of economic cycles accounting for the non-linearity inherent to the alternation between expansions and recessions. First, the dynamic interdependence between the main world economies is rigourously analyzed from intra-group and inter-group perspectives. Moreover, the proposed framework allows us to assess changes in the propagation pattern of business cycles shocks relying on network analysis. Second, after describing the time-varying patterns of global business cycles interdependence, we proceed to explain them with the traditional determinants considered in the business cycle literature. The underlying determinants are identified using a Bayesian Model Averaging (BMA) panel data approach to account for model uncertainty, Moral-Benito (2012). To the best of our knowledge, this is the first study that addresses model uncertainty in identifying the main drivers of business cycle interdependence over time.

Our main results can be summarized as follows. First, we document a structural change in world business cycle synchronization. Specifically, global interdependence has significantly increased during the recent globalization period, since the early 2000s.[1] Second, in addressing which countries have contributed the most to such increase, we perform a cluster analysis and find that countries can be grouped into four clusters, relatively stable over time: an Euro area cluster, an Anglo-Saxon cluster, an Asian Tigers cluster, and an emerging markets cluster. Unlike the results documented in Kose et al. (2012), we find that the significant increase in global business cycle interdependence is mainly attributed to the emerging markets. This is explained by the higher business cycle synchronization of emerging economies with the rest of the world since the early 2000s. Third, a network analysis of the transmission of business cycle shocks discloses that when countries become more synchronized with the rest of the world, they are more prone to recessionary phases than to expansionary phases. Fourth, the most robust determinants of business cycle co-movement before the structural change in global interdependence are financial openness, bilateral trade, government expenditure, liquid liabilities and human capital. Fifth, the break in global interdependence is mainly explained by decreasing differences in sectoral composition among countries, specifically in the agricultural component.

In what follows, in section 2 we study the changes of business cycles interdependence and assess their main source. In section 3, we focus on assessing the factors driving the changes in global business cycle interdependence. Finally, section 4 concludes the paper.

2 Changes in Business Cycles Interdependence

This section provides a comprehensive analysis of the time-varying interdependence among the business cycles of the major world economies listed in Table 1. Unlike previous related

[1] This result is consistent with Canova and Schlaepfer (2013) and Imbs (2006).

studies, we rely on measures of synchronization that allow for non-linear dynamics inherent in expansionary and recessionary phases. First, we construct pairwise and global synchronization measures to assess potential changes in the overall interdependence among countries over time. Second, we classify countries based on their cyclical fluctuations and assess the main sources of changes in global interdependence from a country perspective. Third, we use methods for social network analysis to evaluate the relative influence of each country on the dynamics of world business cycles.

2.1 Measuring Global Synchronization

We rely on the approach of Leiva-Leon (2014) to evaluate changes in the synchronization of business cycles phases. This methodology allows us to measure the synchronization in economic cycles between pair of countries over time, taking into account the asymmetric nature of business cycles, i.e., non-linear dynamics.[2] The methodology consists in assessing the time-varying dependency relationship between the latent variables governing bivariate Markov-switching specifications.

$$\begin{bmatrix} y_{a,t} \\ y_{b,t} \end{bmatrix} = \begin{bmatrix} \mu_{a,0} + \mu_{a,1} s_{a,t} \\ \mu_{b,0} + \mu_{b,1} s_{b,t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{a,t} \\ \varepsilon_{b,t} \end{bmatrix}, \tag{1}$$

where $y_{i,t}$ is the real GDP growth rate of country i; $s_{i,t}$ is an unobservable state variable that indicates the phase of $y_{i,t}$, for $i = a, b$; and $\varepsilon_t \sim N(\mathbf{0}, \Omega)$, where $\varepsilon_t = [\varepsilon_{a,t}, \varepsilon_{a,t}]'$. The state variables $s_{a,t}$ and $s_{b,t}$ evolve according to first-order Markov chains with transition probabilities:

$$p\left(s_{k,t} = j_k | s_{k,t-1} = i_k\right) = p_{ij}^k, \text{ for } i_k, j_k = 0, 1 \text{ and } k = a, b. \tag{2}$$

The expected growth of country i during a recessionary phase, i.e., when $s_{i,t} = 0$, is given by $E(y_{i,t}|s_{i,t} = 0) = \mu_{i,0}$, while its growth in expansionary phase, i.e., when $s_{i,t} = 1$, is $E(y_{i,t}|s_{i,t} = 1) = \mu_{i,0} + \mu_{i,1}$, for $i = a, b$. The primary aim of the framework is to obtain the synchronization between the state variables $s_{a,t}$ and $s_{b,t}$ in order to assess whether countries a and b share the same business cycle phase at time t:

$$sync(s_{a,t}, s_{b,t}) = p\left(s_{a,t} = s_{b,t}\right), \text{ for } t = 1, ..., T. \tag{3}$$

[2] Using Monte Carlo experiments and an application for the economic activity of U.S. states, Leiva-Leon (2014) shows that this methodology is useful for tracking changes in synchronization. This framework is also applied to analyze the interdependence among U.S. industrial cycles in Camacho and Leiva-Leon (2014).

Although the relationship between $s_{a,t}$ and $s_{b,t}$ is unknown, we can model the two extreme cases, as in Harding and Pagan (2006), and express the joint probability of the state variables as follows:

i) If $s_{a,t}$ and $s_{b,t}$ are fully independent, then

$$p\left(s_{a,t} = j_a, s_{b,t} = j_b\right) = p\left(s_{a,t} = j_a\right) p\left(s_{b,t} = j_b\right). \tag{4}$$

ii) If $s_{a,t}$ and $s_{b,t}$ are totally dependent, then $s_{a,t} = s_{b,t} = \varsigma_{ab,t}$; hence,

$$p\left(s_{a,t} = j_a, s_{b,t} = j_b\right) = p\left(\varsigma_{ab,t} = j_{ab}\right). \tag{5}$$

To infer $p\left(s_{a,t} = j_a, s_{b,t} = j_b\right)$, Leiva-Leon (2014) enlarges the setting by introducing an additional state variable, $v_{ab,t}$, which facilitates the assessment of the dependency relationship between $s_{a,t}$ and $s_{b,t}$. This state variable, $v_{ab,t}$, is defined as:

$$v_{ab,t} = \begin{cases} 0 \text{ If } \; s_{a,t} \text{ and } s_{b,t} \text{ are fully independent} \\ 1 \text{ If } \; s_{a,t} \text{ and } s_{b,t} \text{ are completely dependent} \end{cases}, \tag{6}$$

where $v_{ab,t}$ follows a Markov process with transition probabilities:

$$p\left(v_{ab,t} = j_v | v_{ab,t-1} = i_v\right) = q_{ij}^{ab}, \quad \text{for } i_v, j_v = 0, 1. \tag{7}$$

By relying on the joint probability of $s_{a,t}$ and $s_{b,t}$ conditional on v_t, $p\left(s_{a,t} = j_a, s_{b,t} = j_b | v_{ab,t} = j_v\right)$, inferences regarding the bivariate dynamics of the model in Equation (1) can be expressed as a weighted average between the two extreme cases:

$$p\left(s_{a,t} = j_a, s_{b,t} = j_b\right) = p\left(v_{ab,t} = 1\right) p\left(\varsigma_{ab,t} = j_{ab}\right) + \left(1 - p\left(v_{ab,t} = 1\right)\right) p\left(s_{a,t} = j_a\right) p\left(s_{b,t} = j_b\right), \tag{8}$$

where the weights are endogenously determined by

$$p\left(v_{ab,t} = 1\right) = \delta_t^{a,b}. \tag{9}$$

Notice that if δ_t^{ab} is close to one, then $s_{a,t}$ and $s_{b,t}$ are sharing similar dynamics; by contrast, δ_t^{ab} is close to zero, then $s_{a,t}$ and $s_{b,t}$ are following independent patterns at time t. Therefore, δ_t^{ab} provides a measure of the degree of synchronicity in the business cycle phases between countries a and b for every period of time. The parameters are estimated using Bayesian methods, Gibbs sampling, see Kim and Nelson (1999). The filtering algorithm that is used to obtain the inferences relies on an extension of the Hamilton's (1989) filter. For a detailed description of the filtering algorithm, see the appendix A.

To illustrate how the model's output should be interpreted, we present two cases. First, we analyze the case of Canada and Mexico, shown in Figure 1. The input of the model consists in the real GDP growth of both countries, $y_{CA,t}$ and $y_{MX,t}$, while the model's output consists in the recession probabilities for Canada and Mexico and the time-varying synchronization of their cycles, $\delta_t^{CA,MX}$, which has significantly increased during the recent globalization era, i.e., from 1995 onward. Before 1995, both economies experienced expansions and recessions at different points of time. However, after 1995, the probability of recession was low in both countries, and it simultaneously increased during the Great Recession of 2008-2009, as can be observed in the top right chart of the figure. This increase in synchronization may be highly influenced by the North American Free Trade Agreement, which came into force on January 1994.

We also analyze the case of Australia and New Zealand, shown in Figure 2. These economies experimented low levels of synchronization during the 1980s, but from the 1990s onward, their business cycle phases tend to coincide. This is reflected in the increased synchronization plotted in the bottom right chart of Figure 2. Such increase in synchronization may be associated with the total elimination of tariffs or quantitative restrictions in the Closer Economic Relations Trade Agreement between Australia and New Zealand, signed on July 1990.

This analysis is relevant if policy makers are focused on a specific pair of countries.[3] However, since our interest is placed on "the big picture" of global synchronization's evolution, we summarize the results of the 903 pairwise models in a single index obtained by using all the synchronization measures, $\delta_t^{a,b}$ for $a \neq b$. As these synchronization measures are estimated variables from Markov processes, we rely on simple non-parametric approaches to combine them without making any distributional assumptions. The simplest way to create a single index to measure global business cycle interdependence is by averaging the level of synchronization for all the 903 pairwise models:

$$f_t^a = \frac{1}{L} \sum_{l=1}^{L} \delta_t^l, \tag{10}$$

for $l = 1, ..., L$, where l denotes the l-th pairwise model, n is the number of countries, $L = n(n-1)/2$, and f_t^a represents the *average* synchronization. For robustness, we also consider another measure, which consists on extracting the common variation from the synchronization measures by using principal component analysis:

$$\delta_t^l = \lambda_l f_t^c + u_{l,t}, \tag{11}$$

[3]The results for all the possible pairs of countries listed in Table 1 are not reported to save space, since we estimate 903 different pairwise models ($C_2^{43} = 903$). However, these results are available upon request.

for $l = 1, ..., L$, where λ_l are the factor loadings, $u_{l,t}$ has a zero mean and an unknown diagonal covariance matrix and f_t^c is the first principal component, which accounts for most of the variation in the data and therefore represents *common* synchronization.[4]

The two indexes of global synchronization, plotted in Figure 3, show similar patterns. Until the late 1990s, global business cycle synchronization was relatively low and stable; however, in the early 2000s, it started to continuously increase, reaching its maximum level at the end of 2008, i.e., in the middle of the last global recession, as dated by the IMF. These findings imply that world economic activity has become more synchronized during the last two decades, suggesting a change in the propagation of business cycle shocks among countries.

To assess the presence of a structural change in global synchronization from a statistical point of view, we use two different approaches. First, since we are interested in testing a break in the level of f_t^a, and f_t^c, we follow McConnell and Perez-Quiros (2000) and fit each index to a constant, linear trend in two separate models. The results show a positive and statistically significant trend at all levels for both models, with a R^2 equal to 0.76, and 0.77 for the first and second model, respectively. Next, we perform a cumulative sum test (CUSUM test) on the residuals of each model, and find strong evidence of parameter instability in the mean for global synchronization that occurred in the late 2002 for f_t^a and f_t^c, as shown in the charts on the left of Figure 4.[5] Similar results were obtained by removing the linear trend and fitting each index to a constant. As a measure of robustness in analyzing the presence of a structural break in global synchronization, we also infer changes in the level of global synchronization by fitting each index to a two-state Markov-switching mean based on a univariate version of Equation (1). The charts on the right of Figure 4 show the estimated probability of a high mean, along with the corresponding index. The results provide clear evidence of a phase change, from a low to a high mean, that occurred in 2000 for f_t^a and in 2002 for f_t^c. The divergence regarding the exact date of the break can be interpreted as a transition period starting in 2000 and ending in 2002. This result confirms the increase in the world business cycle interdependence during the last decade. The potential factors explaining this change will be evaluated in section 3.

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[4]Given that principal component requires the data to be standardized prior to use, we rescale the extracted factor by using $\frac{f-f_{MIN}}{f_{MAX}-f_{MIN}}$, where f_{MIN} is the factor with the minimum variance and f_{MAX} is the factor with the largest variance, the first factor. This transformation makes the index belong to the unit interval to facilitate interpretation. This has no effect on any of the subsequent results obtained from the use of index.

[5]The CUSUM test is based on the cumulative sum of the one-step ahead forecast error resulting from a recursive estimation. Instability in the parameters of the mean is indicated if the cumulative sum falls outside the area between the two critical lines.

2.2 Source of the Break in Global Interdependence

The purpose of this section is to assess the main source of the increase in global synchronization from the country perspective. Specifically, we are interested in identifying the set of countries that have contributed the most to the significant increment in global interdependence. For this purpose, first, we analyze whether there are groups of countries experiencing similar business cycle patterns. Moreover, based on the dynamic synchronization measures, described in section 2.1, we can evaluate the stability of such groups over time. Second, we analyze the evolution of the interdependence between groups of countries, from a global perspective, and infer the group(s) mainly driving of the increase in global interdependence.

2.2.1 Intra-group Interdependence

We use an agglomerative hierarchical cluster tree (Ward's (1963) linkage method) to identify groups of countries with similar dynamics in their business cycle phases and to examine the evolution of these clusters across time. As the Ward's linkage method uses a distance measure to group countries into different clusters, we convert the synchronization measures, $\delta_t^{a,b}$, into de-synchronization measures as follows:

$$\gamma_t^{a,b} = 1 - \delta_t^{a,b}. \tag{12}$$

where the de-synchronization index, $\gamma_t^{a,b}$, may be interpreted as the cyclical distance. A detailed description of the clustering approach is provided in Appendix B.

The cluster analysis is summarized in dendrograms. Using the transition probabilities in Equation (7), we compute the ergodic measure, $\bar{\delta}^{a,b}$, which can be interpreted as the "average" synchronization between countries a and b for the entire sample period (1981-2013). Then, we obtain the ergodic distance, $\bar{\gamma}^{ab}$, and use this measure to create a dendrogram that represents the average clustering configuration of countries, shown in the top chart of Figure 5.[6] The height of each tree determines the different clusters, i.e., the height of the inverted U represents the level of dissimilarity between two countries or clusters.

We find that there are at least four groups of countries with similar patterns of business cycle synchronization. First, there is a cluster comprising Belgium, Italy, Austria, Netherlands, Germany, Denmark, Luxembourg, Spain, France, Portugal, Ireland, and Greece. Since all these countries, except Denmark, share the same currency, we define this group as the "Euro area

[6]The ergodic probabilities are computed as $\bar{\delta}_i^{a,b} = (1-q_{00}^{ab})/(2-q_{00}^{ab}-q_{11}^{ab})$, where q_{ij}^{ab} represents the estimated transition probabilities associated with the state variable, v_t, that measures synchronization.

cluster". The second group comprises Hong Kong, Japan, South Korea, Thailand, Indonesia, Singapore, Taiwan, and Turkey. Given that most of these Asiatic nations have recently enjoyed a dramatic economic upswing, we call this group the "Asian Tigers cluster". The largest cluster includes Argentina, Venezuela, Brazil, Chile, Mexico, Bulgaria, Romania, China, Philippines, Malaysia, South Africa, Iceland, and Norway. With the exception of Iceland and Norway, these countries are considered by the IMF to be emerging economies, so we call this group the "emerging markets cluster". The last group comprises the U.S., the U.K., Canada, Australia, New Zealand, Finland, Sweden, Switzerland, and Iraq. This cluster consists of mostly advanced Anglo-Saxon countries and some European countries; hence, we define this group as the "Anglo-Saxon cluster". This clustering analysis provides a reasonable description of how countries share similar expansions and recessions and shows that geographic and cultural factors are important factors driving economic interdependence among countries within the Euro area, Asian Tigers, and Anglo-Saxon clusters. The existence of an emerging market cluster also suggests that countries' level of economic development is an important factor explaining business cycle co-movement.

We also assess whether the increase in global synchronization has led to changes in the clustering patterns of countries. For this purpose, we take the average of the cyclical distance over time for the period of low global synchronization (1981-2002) and for the period of high global synchronization (2003-2013). Then, we compute the dendrograms shown in the middle and bottom charts of Figure 5. The clustering analysis in these two sub-samples periods reveals that the Euro area and Anglo-Saxon clusters have remained stable, while there has been some redistribution between the emerging markets and Asian Tigers clusters. This is the case for Brazil and Chile, which became more synchronized with countries in the Asian Tigers cluster. One possible factor explaining the redistribution between the emerging markets and Asian Tigers clusters is the increase in bilateral trade among these countries during the recent globalization era, most notably in the trade of commodities. Apart from this redistribution, the overall composition of the four clusters prevails despite the increase in global business cycle synchronization. Thus, economies have become more synchronized, but their clustering patterns remain stable over time.

2.2.2 Inter-Group Interdependence

Once groups experiencing similar cyclical fluctuations have been identified, our next goal is to analyze how the interdependence among these groups has evolved over time in order to examine where the increase in global business cycle interdependence is coming from.

For this purpose, we rely on multidimensional scaling maps. This techniques consists on projecting the business cycle distances among the N countries in a map in such a way that the Euclidean distances among the countries plotted in the plane approximate the business cycle dissimilarities. In the resulting map, countries that exhibit large business cycle dissimilarities have representations in the plane that are far away from each other. Moreover, we use the time-varying business cycle distances, $\gamma_t^{a,b}$, to create a sequence of maps, one for each t, that can helps us to analyze the dynamic evolution of the interdependence of countries and groups of countries and to disentangle the main source of the increase in global synchronization. A detailed description of Dynamic Multidimensional Scaling (DMS) analysis is provided in Appendix C.

Figure 6 plots the maps for selected periods during global recessions, as dated by the IMF. For illustration purposes only, we draw a link between countries a and b if their business cycle synchronization during period t is larger than 0.5, i.e., $\delta_t^{a,b} > 0.5$. The distance between the countries in the graph approximates their business cycle synchronization, so the closer two countries in each graph are, the more synchronized they are. Notice that the depiction in the figure coincides fairly well with the clustering patterns obtained in section 2.2.

During early 1980s global recession (top right chart of Figure 6), the Euro area cluster shows the highest within-group interdependence, followed by the Asian Tigers cluster. Notice that these two clusters also show high inter-group interdependence. For the early 1990s global recession (top left chart), the Euro area and Asian Tigers clusters remain highly connected, but the interdependence among the Euro area and the Anglo-Saxon clusters increases. However, most of the emerging markets remain isolated, as is the case for Mexico, Malaysia, and Turkey, among others. In the early 2000s global recession (bottom right chart), the picture changes considerably, showing a more connected map. The Euro area, Asian Tigers and Anglo-Saxon clusters continue to be highly related, but most of the countries in the emerging markets cluster, which is the largest cluster, become more interdependent with the rest of the world. Notice that this period corresponds to the transition from low to high global synchronization, as discussed in section 2.1. Thus, this increase in global business cycle interdependence can be mainly attributed to emerging economies. During the Great Recession (bottom left chart), the map experiences the highest connectivity, which is consistent with the propagation of contractionary shocks through most of the economies during that period. For the sake of brevity, we do not present the charts for all the world business cycle maps for every quarter from 1980 to 2013.[7]

[7]However, the complete sequence is available at the authors' website. We use all the charts of the different

Unlike Kose et al. (2012), who find business cycle convergence within groups of industrial and emerging market economies but divergence between both groups, we obtain that the main source of the significant increase in global business cycle synchronization are the emerging market economies. The countries in this cluster experienced independent cyclical patterns until the late 1990s. However, since the early 2000s, they became more synchronized with each other and with the rest of clusters. The main differences between the analysis in Kose et al. (2012) and ours are the following: first, they rely on a linear framework to assess synchronization, while we use nonlinear models to account for the asymmetric nature of the business cycle. Second, their definition of clusters is exogenously predetermined, while we endogenously assign countries to clusters experiencing similar cyclical fluctuations. Third, they rely on arbitrary partitions of the sample to analyze changes in the dynamics, while our approach endogenously assesses time-varying synchronization. Fourth, they use annual data, while we use quarterly data to provide a better identification of expansions and recessions. Notice that a recession is usually defined as two consecutive quarters of negative economic growth, implying that some recessions can be missed when using annual data.

2.3 Transmission of Business Cycle Shocks

World economic interlinkages can be viewed as a complex system comprising a set of elements (countries), in which any pair of elements is subject to some degree of interdependence that may change over time. Although the previous analysis in this paper is based on the results from independent pairwise models, we mitigate the potential shortcomings from this independence assumption by adopting a more integrated perspective. We model world economic interlinkages as a network, g_t, by using the synchronization measures obtained in section 2.1, where each country represents a node and where the probability that two nodes, a and b, are linked at time t is given by $\delta_t^{a,b}$. Thus, the more synchronized the countries are, the higher the degree of connectivity in the network will be. The motivation for adopting this approach is to provide a better understanding of the propagation pattern of business cycle shocks across the major world economies.

We use methods developed for social network analysis to evaluate how a particular economy is simultaneously synchronized with the rest of the economies in the world and to quantify the relative importance of each country in the propagation of shocks to other economies. In

maps periods to create a video that shows the evolution of the world business cycle interdependence from 1980 to 2013. The video can be found at: *https://sites.google.com/site/daniloleivaleon/global-business-cycles* particular, we consider the betweenness centrality, $B_{i,t}$, since this measure can be interpreted as the ability of country i to act as a channel in the transmission of business cycle shocks between other countries in the network g_t during period t. The betweenness centrality is calculated as

$$B_{i,t} = \sum_{j \neq k : j,k \neq i} \frac{\tau^i_{j,k}(g_t)}{\tau_{j,k}(g_t)}, \tag{13}$$

where $\tau^i_{j,k}(g_t)$ is the number of shortest paths between j and k in g_t that pass through country i and $\tau_{j,k}(g_t)$ is the total number of shortest paths between j and k in g_t. [8]

To assess the evolution of the countries' centrality over the business cycle, we exogenously define expansionary and recessionary phases for each economy using the Bry-Boschan algorithm. Both time-varying betweenness centrality and recessionary episodes for most of the countries are plotted in Figure 7, showing a close relation between them. For the rest of countries, the centrality was equal to zero for the entire sample period, and therefore not reported.

In general, a country's centrality tends to increase during periods of national recessions, returning to lower levels during economic expansions. This is also the case for the Great Recession (2007-2009) where most of the countries became more central. This finding suggests that when countries become more globally synchronized, they are more prone to contractionary phases than to expansionary phases, which is consistent with the view that economies tend to become more synchronized during recessions than during expansions. However, notice that the degree of centrality also varies across nations. The countries with the highest centrality over time are Japan, Hong Kong, France, and Austria, while the countries with the low centrality are Portugal, Turkey, Iceland, and Bulgaria.

We also compute the average centrality across countries, which can be interpreted as a global measure of the transmission of business cycle shocks. We define the global centrality as,

$$B_t = \frac{\sum_i B_{i,t}}{n}, \tag{14}$$

where $B_{i,t}$ is the time-varying betweenness centrality and n is the number of countries. The global centrality is plotted in Figure 8 and provides similar information to the country-specific cases. Accordingly, it tends to increase during periods of global recessions, as defined by the IMF, reaching its maximum level during the Great Recession. This result is observed because higher global centrality increases the likelihood that country-specific shocks are transmitted to the rest of economies in the world.

[8] A shortest path between two countries a and b in the weighted global business cycle network, g_t, is simply a directed path from a to b with the property that no other such path has a lower weight.

3 What Does Explain the Increase in Synchronization?

In section 2.1, we document the existence of a structural break in global business cycle synchronization at the beginning of the 21^{st} century. The clustering analysis presented in section 2.2.1 also suggests that the increase in global business cycle synchronization is mainly driven by emerging economies. In this section, we identify the underlying factors explaining the structural break in global business cycle interdependence by using a BMA approach to account for model uncertainty. Since there are different theories suggesting different potential determinants of business cycle synchronization, we are not certain about the true model specification governing business cycle interdependence. The BMA approach allows us to deal with that uncertainty. To the best of our knowledge, this is the first study to address model uncertainty in the identification of the main drivers of business cycle interdependence over time.

3.1 Data

Previous studies in the literature have obtained different results depending on the data, methodology, and variables considered. However, at least three factors are considered in most empirical studies on business cycle co-movement: international trade, specialization, and financial factors. In addition to these standard potential determinants, we follow Baxter and Kouparitsas (2005) and include factor endowments into our analysis. We also propose as a new potential determinant common fiscal policy. We focus on explaining changes in business cycle interdependence based on within-variation across time; thus, we consider only time-varying factors. The data are collected for the 1981-2010 period at an annual frequency.[9] We describe in details the measurement of the potential determinants as follows:

- **International trade**. In theory, trade positively affects business cycle synchronization, as shocks are transmitted between countries through their trade flows. This positive relationship between trade and business cycle co-movement is predicted by a number of theoretical models, such as those of Canova and Dellas (1993) and Kose and Yi (2001, 2006).[10] This trade channel is captured in our analysis by including the bilateral trade measure used in Frankel and Rose (1998),

$$T_{ab,t} = \frac{E_{a,b,t} + I_{a,b,t}}{GDP_{a,t} + GDP_{b,t}} \tag{15}$$

[9] Definitions for all the variables are provided in Appendix D.

[10] Evidence of the positive relationship between trade intensity and business cycle synchronization is found in Frankel and Rose (1998), Imbs(2004), Baxter and Kouparitsas (2005), and Calderon et al. (2007), among others.

where $E_{a,b,t}$ denotes total exports from country a to country b in year t, $I_{a,b,t}$ denotes imports to country a from country b in year t, and $GDP_{a,t}$ is the nominal GDP in country a in year t. Bilateral trade data are taken from the IMF's Direction of Trade Statistics.[11]

- **Specialization**. Similarity in industrial composition proxies for the specialization patterns in both countries. We expect two economies with a similar sectoral composition to have high business cycle interdependence since sector-specific shocks could be rapidly transmitted from one economy to the other (Imbs, 2004).

  To capture differences in the sectoral composition between two countries, we use agriculture, industry, and services real value added, and following the computation in Imbs (2004):

$$S_{ab,t} = \sum_{k=1}^{n} |S^k_{a,t} - S^k_{b,t}|, \tag{16}$$

  where $S^k_{a,t}$ is the GDP share of sector k in country a during period t. This index takes a value from 0 (completely similar structures) to 2 (completely different structures).[12]

- **Financial factors:** financial openness, private credit issued by deposit money banks and other financial institutions to GDP, financial system deposits to GDP, and liquid liabilities to GDP. These variables proxy for financial integration.

  In theory, the effect of financial integration on business cycle synchronization is ambiguous and depends on the transmission mechanism of the shocks. In periods of high financial integration, negative shocks to firm productivity in a particular country will induce banks to decrease lending in these countries but increase lending in unaffected countries (Morgan et al., 2004), which may have a negative effect on the business cycle synchronization of these economies. On the other hand, a negative shock to the banking sector may be transferred to the other countries, since banks will reduce lending globally to shrink their balance sheets because of their lower net worth, thereby increasing business cycle co-movement (Morgan et al., 2004, Kalemli-Ozcan et al., 2013b).

  As a measure of financial openness, we use

$$F_{ab,t} = \frac{A_{a,t} + L_{a,t}}{GDP_{a,t}} + \frac{A_{b,t} + L_{b,t}}{GDP_{b,t}} \tag{17}$$

[11] For robustness, we also use the trade intensity measure in Deardoff (1998). The results of the analysis using this alternative measure of bilateral trade intensity remain quantitatively unchanged and are available upon request.

[12] Agriculture, service, and industrial value added are taken from the World Development Indicators.

where $A_{a,t}$ is total assets to GDP and $L_{a,t}$ is liquid liabilities to GDP in country a.

For private credit to GDP, financial system deposits to GDP and liquid liabilities to GDP, we transform the variables to capture dissimilarities between two countries, a and b, since we aim to explain de-synchronization among countries, $\gamma_t^{a,b}$, as defined in Equation (12). In particular, we compute the absolute value of the difference in financial factor x between country a and country b.

$$x_{ab,t} = |x_{a,t} - x_{b,t}|. \tag{18}$$

where $x_{a,t}$ is a financial variable in country a at period t and $x_{b,t}$ is the same financial variable in country b at the same time period, t.

- **Factor endowments**. We consider two main factors of production: labor, proxied by human capital and the proportion of a country's population living in urban areas, and capital, proxied by the per capita capital stock. As Baxter and Kouparitsas (2005) pointed out, economic theories, including the standard Heckscher-Ohlin theory and Ricardian theories, predict a relationship between factor endowments, trade and business-cycle co-movements.

  Human capital proxies for skilled and unskilled labor. Dellas and Sakellaris (2003) find that schooling is countercyclical owing to higher opportunity cost during expansions. These higher costs lead to substitution between human capital investment and competing economic activities. Thus, we expect similarities in human capital indexes between two countries to be associated with higher business cycle co-movement.[13] The proportion of a country's population living in urban areas also capture different labor skills.[14]

  We use the absolute value of the difference in endowment factors, z, to capture dissimilarities in factors of production between country a and country b at period t,

$$z_{ab,t} = |z_{a,t} - z_{b,t}|. \tag{19}$$

  where $z_{a,t}$ is a factor endowment in country a at t and $z_{b,t}$ is the same factor endowment in country b at the same period t.

- **Common fiscal policy**. The Eurozone sovereign debt crisis that started in Greece at the end of 2009 and subsequently spread to Ireland, Portugal and Spain suggest that two

[13]We take the log of the human capital index before computing the absolute difference. The other determinants are expressed in percentages; thus, we use the direct differences.

[14]Urban population is also highly correlated with the level of income of a country (Bloom et al., 2008). Differences in urban population could also capture different level of economic development.

economies with high level of debts and fiscal deficit are more likely to be in recession than two economies that diverge in their level of debt or deficit. Thus, we consider as an additional potential determinant of business cycle synchronization dissimilarities in fiscal policy. We measure this dissimilarity using the absolute value of the difference in government expenditure (share of GDP) between two countries.

In the next section, we briefly present the BMA approach used to infer the most robust factors correlated with business cycles interdependences.

3.2 Methodology

To address model uncertainty and unobserved time-invariant pairwise factors, we use a BMA panel data approach. The pairwise de-synchronization model is defined as

$$\gamma_{ab,t} = x'^{k}_{ab,t}\beta^k + \eta_{ab} + \mu_t + \upsilon_{ab,t}, \tag{20}$$

where $\gamma_{ab,t}$ is the distance or de-synchronization between the business cycle of countries a and b, and $x'^{k}_{ab,t}$ includes a set of potential determinants, as described in section 3.1. The pairwise country fixed effects, η_{ab}, capture time-invariant unobservable factors in both countries.

We examine the stationary properties of our determinants by using the Harris-Tzavalis (1999) unit-root test to avoid spurious inference.[15] Table 2 shows that our main variable of interest, business cycle de-synchronization, follows a unit root process. Other variables, such as financial openness, bilateral trade, differences in human capital, capital stock per capita, financial deposit to GDP, private credit to GDP, and urban population, also present a unit root. Therefore, we use the first-difference transformation to eliminate the pairwise country fixed effects. Unobserved common factors are captured in μ_t and are eliminated by cross-sectionally demeaning the data.

The key question is as follows: Which variables $x'^{k}_{ab,t}$ should be incorporated into the model? BMA addresses model uncertainty by estimating models for all possible combinations of the regressors and by taking a weighted average over all the candidate models, where the weights are determined by Bayes' rule. The probability that model j, M_j, is the "true" model given the data, y, i.e., the posterior model distribution given a prior model probability, is defined as

$$P(M_j|y) = \frac{P(y|M_j)P(M_j)}{\sum_{i=1}^{2^k} P(y|M_i)P(M_i)}, \tag{21}$$

[15]This test assumes that the number of periods, T, is small and that the number of panels, N, is large. The main shortcoming of this test is that it imposes the same autoregressive parameter on all the panels.

where $P(y|M_j)$ is the marginal likelihood of Model j, $P(M_i)$ is the prior model probability, and $\sum_{i=1}^{2^k} P(y|M_i)P(M_i)$ is the integrated likelihood of model j. We consider an estimation framework with a Bayesian linear regression and Zellner's g-prior and assume a hyper-g-prior.[16]

We are interested in the posterior inclusion probability (PIP) of a variable h, which is defined as

$$P(\theta_h \neq 0|y) = \sum_{\theta_h \neq 0} P(M_k|y), \tag{22}$$

where θ_h contains the coefficients of the regressor set that defines model h according to equation (20). The PIP is interpreted as the probability that a particular variable h belongs to the true pairwise business cycle de-synchronization model. In the next section, we present the PIP of all the potential determinants of business cycle de-synchronization across different periods.

3.3 Results

As we show in Figures 3 and 4, global business cycle interdependence has significantly increased since the beginning of recent globalization era, after a structural break that occurred in the early 2000s. To assess the main factors explaining the structural break, we split the sample into two periods. Since the exact timing of the break is unclear, in Table 3, we report the results of the BMA panel analysis for different partitions of the sample, i.e., assuming that the break occurred in 2000, 2001, 2002, 2003 or 2004.[17] Rows 2-11 of the table present the posterior inclusion probability of each potential determinant of time-varying business cycle de-synchronization for different periods before the break. We find that the most robust determinants of business cycle synchronization during this period are financial openness, differences in government expenditure, bilateral trade, differences in liquid liabilities, and differences in human capital indexes between the two countries. Although we cannot claim any causal relationship between these determinants and business cycle de-synchronization, because of simultaneity bias and reverse

[16]For a detailed discussion of the use of Zellners g-prior and the hyper-g-prior, see Ley and Steel (2012). The advantage of using a mixture of g-priors, such as the hyper-g prior, is that the hyperparameter g is not fixed across all the candidate models, but it is adjusted by using Bayesian updating. Recently, Ley and Steel (2012) have shown that hyper-g-prior outperforms fixed g-priors. We also need to specify a prior on the model space, $P(M)$. Ley and Steel (2009) propose the use of a beta-binomial prior, as it reduces the effect of imposing a particular prior model size on the posterior probabilities. This prior only requires the selection of the prior expected model size.

[17]Some of the determinants were not available over the whole sample period for some countries. To avoid losing other determinants, we excluded the countries for which the determinant was missing for a particular period from the sample. These countries are Hong Kong, Taiwan, Luxembourg, Germany, Greece, Belgium, Iraq, Romania, Venezuela, Chile, Bulgaria, China, and the United Kingdom.

causality, we find that all these determinants affect business cycle de-synchronization with the expected sign.[18] The importance of financial openness and liquid liabilities to explain variation in business cycle synchronization is consistent with the recent empirical findings by Kalemli-Ozcan et al. (2013a), who showed that cross-border banking integration between two countries is related to co-movement of output. The high PIP of bilateral trade is consistent with previous studies in the literature showing that trade transmits shocks and synchronizes economies across borders (Frankel and Rose (1998), Imbs (2004), Baxter and Kouparitsas (2005), among many others). Human capital index is a factor endowment considered by Baxter and Kouparitsas (2005), who found that schooling is not a robust factor of business cycle co-movement. In contrast to their study, we find that countries with different levels of schooling are more likely to be in different business cycle phases, at least before the structural break of global business synchronization.[19] Finally, our study is the first to document the importance of common fiscal policy (government expenditure share of GDP) as a robust determinant of business cycle synchronization. If countries experience similar increases in government purchases or decrease in taxes, they tend to be associated with similar business cycle fluctuations.

Surprisingly, we find that after the break (see rows 13-22 of Table 3), i.e., during the recent globalization era, the only robust determinant is similarity in sectoral composition. Acemoglu et al. (2012) study the importance of sectoral composition in the formation of business cycles and show that in the presence of intersectoral input-output linkages, microeconomic idiosyncratic shocks may lead to aggregate fluctuations. In addition, Camacho and Leiva-Leon (2014) find evidence of a cascade effect in the transmission of sectoral business cycle shocks. At the aggregate level, if similarity in the sectoral composition of countries in the major world economies increases, business cycle shocks can be more rapidly transmitted from one country to another, increasing global business cycle interdependence.

Table 4 presents the results of the BMA in a dynamic panel setting that includes two lags of the de-synchronization index as regressors. The number of lags was selected according to the posterior inclusion probability criteria.[20] The results show that the main determinants of business cycle interdependence, before and after the break, are robust to the inclusion of lags of the dependent variable. These results imply that the significant increase in global economic cycles interdependence occurred in the early 2000s is closely associated with the similarity in

[18] Results about the posterior mean and standard deviation are available upon request.

[19] Our human capital indexes mainly measure the number of enrolments in high school and tertiary education.

[20] We also consider specifications with a different number of lags of the de-synchronization index, but the posterior inclusion probability of any additional lag was low.

the sectoral composition of the main world economies.

3.4 Robustness

In this subsection, we check the robustness of the results obtained with the BMA to the assumptions made in the identification of the main drivers of business cycle interdependence. First, we present results for an analysis using a different prior for the hyperparameter g; for this purpose, we adopt the BRIC prior introduced by Fernandez et al. (2001), which sets $g = max(N, K^2)$. The results show that although the probabilities of inclusion are less conservative, the main findings are robust to the specification of the prior. The tables containing the results of this subsection are reported in Appendix E for the sake of space. The most robust determinants of fluctuations in business cycle synchronization are the same as those obtained by using the hyper-g prior in the static panel and in the dynamic panel models (see Tables I and II of Appendix E, respectively). The only exception is that the posterior inclusion probabilities of bilateral trade and liquid liabilities are now significantly lower. We also find that after the break, the most important determinant is similarity in sectoral composition.

Second, we also check the robustness of our results to use of the Bayesian model averaging technique adopted in the main analysis. In particular, to identify the main determinants of dynamic business cycle interdependence, we consider a Bayesian combination of frequentist estimators, the weighted-average least squares (WALS) method introduced by Magnus et al. (2010). The WALS estimator relies on an orthogonalization of the regressors such that they are independent from one another. This orthogonal transformation allows us to consider prior distributions that are more consistent with our ignorance regarding the importance of each potential determinant in explaining business cycle interdependence and substantially reduces the computational time of this model-averaging technique.

The results presented in Table III and Table IV show that the main determinants are the same as the determinants obtained by using the BMA approach with the static and dynamic panel models, respectively. As a rule of thumb, a determinant is considered robust using the WALS estimator if the t-statitics is above 2 in absolute value. Therefore, our results are robust to the use of different g-priors and model averaging techniques.

3.5 Sectoral Composition and Global Interdependence

The findings of the BMA reported in tables 3 and 4 show that dissimilarity of sectoral composition is the main driver of business cycle synchronization after the structural break in global business cycle synchronization. To understand which is the sector that contributed the most to explain variation in business cycle synchronization, we divide dissimilarity of sectoral composition into three different subcomponents: difference in agriculture share, difference in industry share, and difference in service share. In table 5, we provide results of the BMA approach (dynamic panel) using the three sectoral variables as potential determinants instead of the dissimilarity of sectoral composition. The findings show that the most robust correlated factor with business cycle synchronization after the break, is the difference in agriculture share to GDP between the two economies. The posterior mean of agriculture share is 0.5873 and the posterior standard deviation is 0.1329, suggesting that larger differences in agriculture are associated to higher business cycle de-synchronization (lower business cycle synchronization). This implies that, pairs of countries that experienced an increasing degree of synchronization in their business cycles around the early 2000s, should have experienced lower differences in agricultural composition around the same (or prior to that) period.

To verify this finding, we separate pairs of countries that experienced an increasing synchronization from pairs of countries that presented a relatively time invariant business cycle synchronization over the full sample period. In order to group pairs of countries based on common temporal patterns in business cycle synchronization we use the K-Spectral Centroid (K-SC) clustering algorithm (Yang and Leskovec, 2011), which is designed to clusters time series by their shape. The top panels of Figure 9 present the pairwise business cycle synchronizations, $\delta_t^{a,b}$, for the two different groups identified with the K-SC algorithm, i.e. the "Increasing Sync" group and the "Stable Sync" group.[21] One third of all the pairs of countries was allocated to the Increasing Sync group, while the rest of pairs were assigned to the Stable Sync group. The increase in business cycle synchronization after 2000 in the Increasing Sync group confirms the structural break found in section 2.1 (see Figure 9*a*). The bottom panels of Figure 9 show the differences in the disaggregated sectoral composition, i.e. agricultural, industrial, and services, only for the pairs of countries in the Increasing Sync group. As expected, differences in agricultural composition (see Figure 9*c*) decreased significantly since the late 90s. This decrease has been accompanied by an increased in global business cycle synchronization. On the other hand, the differences in the industrial composition have slightly increased from 1995 to 2003 while the differences in services composition remained relatively stable over the sample period, 1980-2010.[22]

[21]In Figure 9 the time series are stacked showing the relative contribution of each element at time t.

[22]Providing an explanation about the mechanism by which sectoral composition, in particular agricultural, strongly influences synchronization of cycles would require a more structural analysis, such as a DSGE modelling

Overall, the empirical analysis shows: i) the existence of a break in global business cycle synchronization lead by a third of all the pairs of countries considered in our sample; ii) that the break is mainly associated to emerging market economies, since they became more synchronized with the rest of the world; and iii) that the break is mainly explained by a decrease in the sectoral composition differences between countries, particularly in the agricultural component.

4 Conclusion

The first part of this paper provides a comprehensive examination of the evolution of business cycle co-movement across 40 developed and developing countries over the period from 1980 to 2013. We apply a novel Markov-switching model to infer the probability that two countries are in the same business cycle phase. This approach accounts for the non-linearity inherent to the dynamics of business cycles. The results show that most of the economies have become more synchronized since the recent globalization era (i.e., from 2000 onward), suggesting that systemic risk has increased during the last decade. We also consider a clustering analysis to evaluate whether there are groups of countries with similar patterns in business cycle co-movement. The clustering analysis reveals at least four groups of countries that are relatively stable over time: the Euro area cluster, the Anglo-Saxon cluster, the Asian Tigers cluster, and the emerging markets cluster. Moreover, the increase in synchronization after 2000 seems to be mainly attributed to the increased synchronization of the emerging market cluster with the rest of the major world economies. We also consider network measures to quantify the degree of synchronization of one economy with the other economies in the world. The network analysis shows that the degree of connectedness of a country with the other countries in the world tends to increase in periods prior to recessions. These findings have important implications for policy makers, who could use the proposed framework to evaluate the degree of exposure that a given country has to external shocks.

The second part of the paper focuses on identifying the most important factors explaining variation in business cycle co-movement before and after the global business cycle synchronization break. As there is no agreement in the business cycle literature about the potential determinants of business cycle synchronization, we rely on a Bayesian model averaging approach to account for model uncertainty. The results suggest that the most robust determinants before the global break are financial openness, government expenditure, and bilateral trade. Other important factors that explain changes in business cycle co-movement are liquid liabilities and

approach, which is out of the scope of this paper and therefore left for further research.

human capital. However, the importance of these determinants, measured by their inclusion probability, varies across time. In particular, we find that the only robust determinant after the increase in global business cycle interdependence is similarity in countries' industrial composition, specifically the difference in agricultural composition.[23]

[23]Future research could focus on the simultaneous estimation of the most important determinants found in this paper: financial openness, bilateral trade, human capital, liquid liabilities, and government share. However, finding time-varying exogenous variation for all these determinants would be challenging.

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Table 1: List of Countries

Country	ISO Code	Country	ISO Code
Argentina	AR	Malaysia	MY
Australia	AU	Mexico	MX
Austria	AT	Netherlands	NL
Belgium	BE	New Zealand	NZ
Brazil	BR	Norway	NO
Bulgaria	BG	Philippines	PH
Canada	CA	Portugal	PT
Chile	CL	Romania	RO
China	CN	Singapore	SG
Denmark	DK	South Africa	ZA
Finland	FI	South Korea	KR
France	FR	Spain	ES
Germany	DE	Sweden	SE
Greece	GR	Switzerland	CH
Hong Kong	HK	Taiwan	TW
Iceland	IS	Thailand	TH
Indonesia	ID	Turkey	TR
Iraq	IQ	United Kingdom	GB
Ireland	IE	United States	US
Italy	IT	Venezuela	VE
Japan	JP	Africa*	AA
Luxembourg	LU		

*Because of the lack of data on real GDP for African countries, this series corresponds to an index of the overall economic activity of Africa.

Table 2: Harris-Tzavalis unit-root test

	(1) test statistic (p-value)
Business Cycle synchronization	0.7584(0.1656)
Financial Openness	0.8566(1.0000)
Human Capital index diff.	0.9543(1.0000)
Bilateral Trade	0.7623(0.3276)
Liquid Liabilities to GDP diff.	0.7231(0.0000)
Financial System Deposit to GDP diff.	0.7715(0.7846)
Capital stock per capita diff.	0.9263(1.0000)
Private Credit to GDP diff.	0.8458(1.0000)
Urban population diff. (% of total population)	0.9161(1.0000)
Difference of sectoral composition	0.7304(0.0000)
Government Expenditure(% of GDP) diff.	0.6627(0.0000)

Time trends are included in all the tests; p-values are presented in parentheses.

Table 3: Determinants of business cycle de-synchronization before and after the break: A BMA approach. Hyper-g-prior. Static panel

PIP Before the Break (period: 1983-)	2000	2001	2002	2003	2004
Financial Openness	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Government Expenditure(% of GDP)	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Bilateral Trade	**0.9991**	**0.9954**	**0.9857**	**0.9932**	**0.9962**
Liquid Liabilities to GDP diff.	**0.9907**	**0.9800**	**0.9915**	**0.9921**	**0.9940**
Human Capital index diff.	**0.9906**	**0.9923**	**0.9887**	**0.9907**	**0.9928**
Difference of sectoral composition	**0.8779**	0.7717	0.7254	**0.8495**	**0.9302**
Private Credit to GDP diff.	0.7890	**0.8902**	**0.8868**	**0.8535**	0.7899
Capital Stock per capita diff.	0.7137	0.6938	0.6195	**0.9012**	**0.9327**
Financial System Deposit to GDP diff.	0.6973	0.5540	0.5327	0.6026	0.6034
Urban population diff. (% of total population)	0.5861	0.5596	0.5374	0.5952	0.5942
PIP After the Break (period: -2010)	2001	2002	2003	2004	2005
Financial Openness	0.4426	0.2533	0.4772	0.4583	0.5279
Government Expenditure(% of GDP)	0.3546	0.1794	0.3171	0.2613	0.2412
Bilateral Trade	0.3197	0.1781	0.3289	0.2549	0.2104
Liquid Liabilities to GDP diff.	0.6612	0.2823	0.6364	0.4442	0.3665
Human Capital index diff.	0.5843	0.4255	0.6877	0.658	0.4258
Difference of sectoral composition	**0.8220**	0.6575	**0.8308**	**0.9973**	**1.0000**
Private Credit to GDP diff.	0.4067	0.1787	0.3353	0.2500	0.3180
Capital Stock per capita diff.	0.3371	0.1859	0.3523	0.2475	0.2081
Financial System Deposit to GDP diff.	0.3198	0.1972	0.3477	0.5452	0.7882
Urban population diff. (% of total population)	0.4449	0.2592	0.3850	0.2887	0.2197

The sample period considered before the break is from 1983 to the year specified in the selected column. After the break, the sample considered is from the year specified in the selected column to 2010. The results are obtained by using 30 developed and developing countries. The dependent variable is distance or de-synchronization of the business cycles of two countries. Most of the regressors capture differences between the countries, except bilateral trade and financial openness. The results are obtained by using a hierarchical prior model and hyper-g-prior. Entries higher than 0.8 are presented in bold.

Table 4: Determinants of business cycle de-synchronization before and after the break: A BMA approach. Hyper-g-prior. Dynamic panel

PIP Before the Break (period: 1983-)	2000	2001	2002	2003	2004
De-synchronization$_{t-1}$	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
De-synchronization$_{t-2}$	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Financial Openness	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Government Expenditure(% of GDP)	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Bilateral Trade	**0.9960**	**0.9820**	**0.8985**	**0.9584**	**0.9730**
Liquid Liabilities to GDP diff.	**0.9797**	**0.9285**	**0.9853**	**0.9872**	**0.9905**
Human Capital index diff.	**0.8947**	**0.9452**	**0.8960**	**0.9304**	**0.9378**
Difference of sectoral composition	0.7730	0.6926	0.7254	**0.8245**	**0.9253**
Private Credit to GDP diff.	0.4210	0.5367	0.5347	0.5239	0.4188
Capital Stock per capita diff.	0.4258	0.5133	0.3679	0.7998	0.7972
Financial System Deposit to GDP diff.	0.3669	0.3263	0.2919	0.3763	0.3573
Urban population diff. (% of total population)	0.3435	0.3242	0.2906	0.3743	0.3566
PIP After the Break (period: -2010)	**2001**	**2002**	**2003**	**2004**	**2005**
De-synchronization$_{t-1}$	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
De-synchronization$_{t-2}$	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Financial Openness	0.2060	0.2533	0.2808	0.2199	0.4563
Government Expenditure(% of GDP)	0.1423	0.1794	0.1674	0.2097	0.3641
Bilateral Trade	0.1271	0.0799	0.1717	0.1220	0.2107
Liquid Liabilities to GDP diff.	0.1710	0.0799	0.4636	0.2205	0.2756
Human Capital index diff.	0.6494	0.4010	**0.8383**	0.6638	0.5730
Difference of sectoral composition	**0.9950**	**0.9990**	**0.9989**	**1.0000**	**1.0000**
Private Credit to GDP diff.	0.1528	0.0800	0.1964	0.1261	0.4020
Capital Stock per capita diff.	0.1163	0.0806	0.1874	0.1297	0.2155
Financial System Deposit to GDP diff.	0.1065	0.0803	0.2318	0.4300	**0.8122**
Urban population diff. (% of total population)	0.2365	0.1176	0.2408	0.1585	0.2272

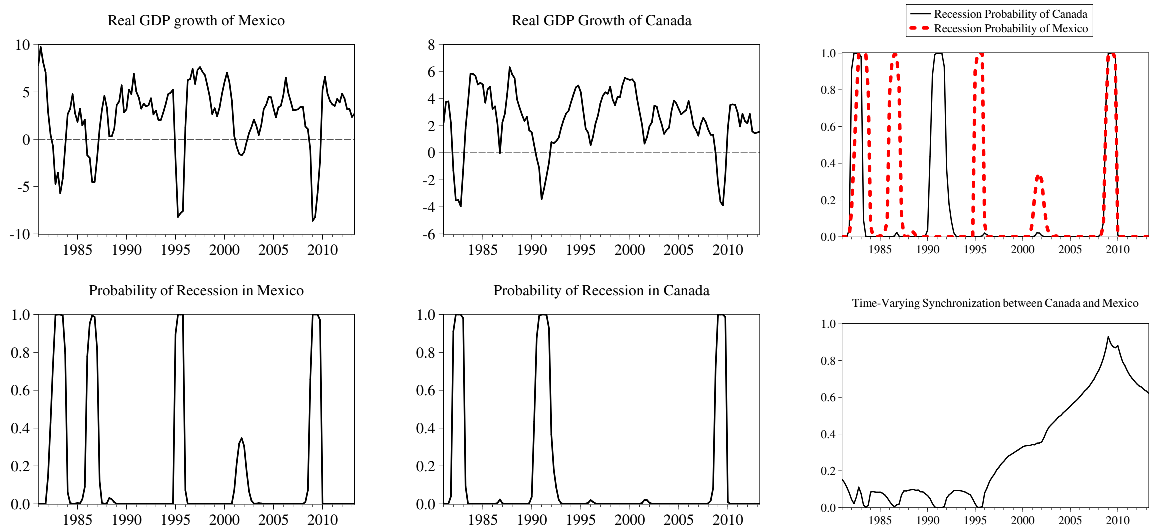
The sample period considered before the break is from 1983 to the year specified in the selected column. After the break, the sample considered is from the year specified in the selected column to 2010. The results are obtained by using 30 developed and developing countries. The dependent variable is distance or de-synchronization of the business cycles of two countries. Most of the regressors capture differences between the countries, except bilateral trade and financial openness. The results are obtained by using a hierarchical prior model and hyper-g-prior. Entries higher than 0.8 are presented in bold.

Table 5: Determinants of business cycle de-synchronization before and after the break including differences in sectors share: A BMA approach. hyper-g prior. Dynamic panel

PIP Before the Break (period: 1983-)	2000	2001	2002	2003	2004
De-synchronization$_{t-1}$	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
De-synchronization$_{t-2}$	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Financial Openness	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Government Expenditure(% of GDP)	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Bilateral Trade	**0.9935**	**0.9734**	**0.8610**	**0.9427**	**0.9627**
Liquid Liabilities to GDP diff.	**0.9656**	**0.8818**	**0.9755**	**0.9770**	**0.9833**
Human Capital index diff.	**0.8451**	**0.9138**	**0.8471**	**0.8928**	**0.9081**
Difference in agriculture share	0.2297	0.3827	0.3973	0.5819	0.5601
Difference in industry share	0.2892	0.2591	0.2338	0.3306	0.3431
Difference in service share	0.6165	0.4646	0.4061	0.5179	0.6618
Private Credit to GDP diff.	0.3043	0.4095	0.4187	0.4071	0.3157
Capital Stock per capita diff.	0.3077	0.3974	0.2702	0.7269	0.7265
Financial System Deposit to GDP diff.	0.2560	0.2239	0.2021	0.2732	0.2636
Urban population diff. (% of total population)	0.2342	0.2215	0.2020	0.2713	0.2618
PIP After the Break (period: -2010)	**2001**	**2002**	**2003**	**2004**	**2005**
De-synchronization$_{t-1}$	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
De-synchronization$_{t-2}$	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Financial Openness	0.1738	0.1485	0.3089	0.2440	0.5002
Government Expenditure(% of GDP)	0.1329	0.1327	0.1978	0.2011	0.3673
Bilateral Trade	0.1004	0.0889	0.1964	0.1479	0.2477
Liquid Liabilities to GDP diff.	0.1425	0.0887	0.5016	0.2527	0.2988
Human Capital index diff.	0.5857	0.4197	**0.8629**	0.7338	0.6069
Difference in agriculture share	0.1327	0.6081	**0.8653**	**0.9991**	**0.9997**
Difference in industry share	0.4261	0.6677	**0.8055**	0.6927	0.6062
Difference in service share	0.6780	0.4262	0.3701	0.4935	0.7855
Private Credit to GDP diff.	0.1234	0.0895	0.2402	0.1509	0.3971
Capital Stock per capita diff.	0.0905	0.0898	0.2210	0.1534	0.2498
Financial System Deposit to GDP diff.	0.0834	0.0890	0.2570	0.5074	**0.8765**
Urban population diff. (% of total population)	0.1851	0.0104	0.2695	0.1848	0.2597

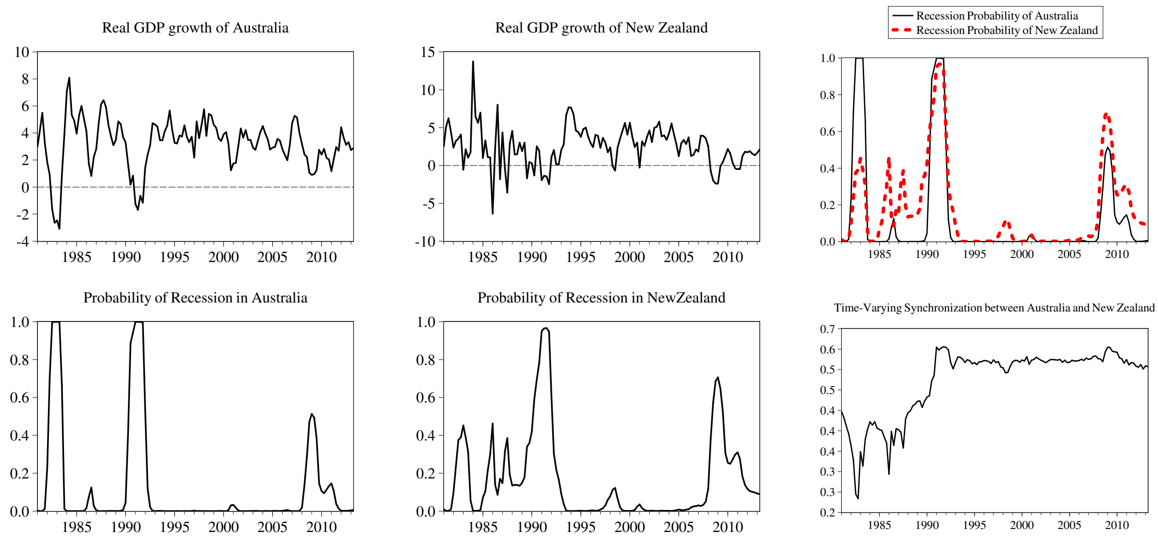
The sample period considered before the break is from 1983 to the year specified in the selected column. After the break, the sample considered is from the year specified in the selected column to 2010. The results are obtained by using 30 developed and developing countries. The dependent variable is distance or de-synchronization of the business cycles of two countries. Most of the regressors capture differences between the countries, except bilateral trade and financial openness. The results are obtained by using a hierarchical prior model and hyper-g-prior. Entries higher than 0.8 are presented in bold.

Figure 1: Business cycle interdependence between Canada and Mexico



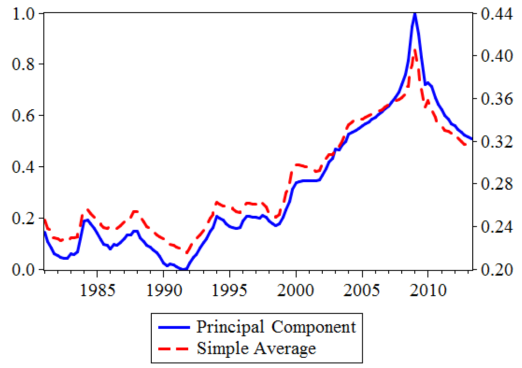
Note: The results shown in the figure come from the bivariate Markov-switching model for the real GDP growth of Mexico and Canada. The sample period is 1981:Q1-2013:Q2.

Figure 2: Business cycle interdependence between Australia and New Zealand



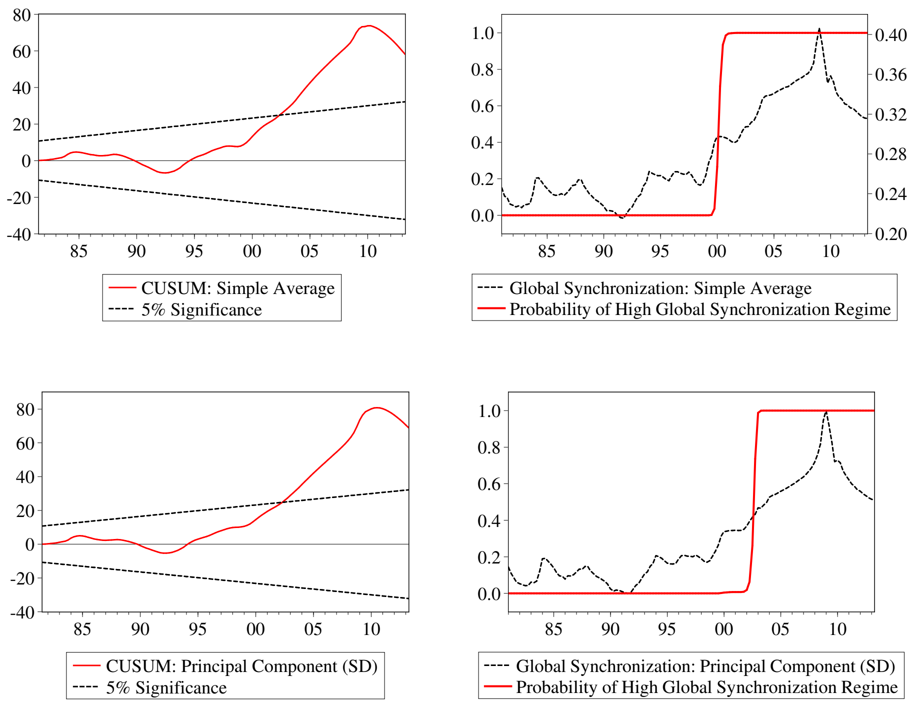
Note: The results shown in the figure come from the bivariate Markov-switching model for the real GDP growth of Australia and New Zealand. The sample period is 1981:Q1-2013:Q2.

Figure 3: Global time-varying synchronization



Note: The solid blue line (left axis) represents an index of global business cycle interdependence obtained by taking the first principal component between each of the pairwise synchronization measures across countries. The dashed red line (right axis) represents an index of global business cycle interdependence obtained by averaging the pairwise synchronization measures across models. The sample period is 1981:Q1-2013:Q2.

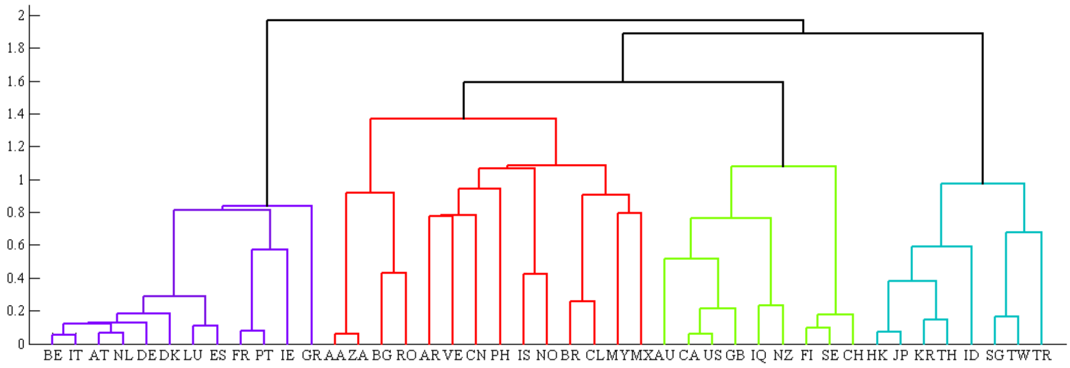
Figure 4: Break in global time-varying synchronization



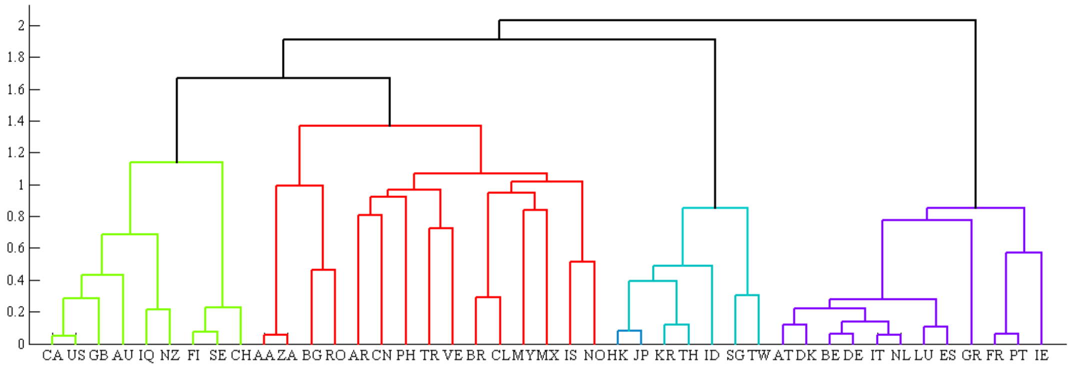
Note: Charts on the left show CUSUM tests for the global interdependence indexes. Charts on the right show the inferences regarding phase changes for the global interdependence indexes. The sample period is 1981:Q1-2013:Q2.

Figure 5: Hierarchical clustering from business cycle interdependence

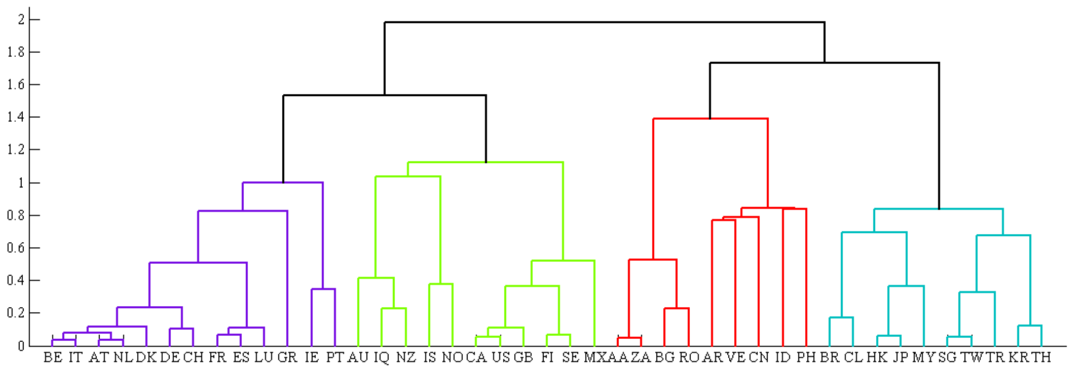
1981-2013



1981-2002

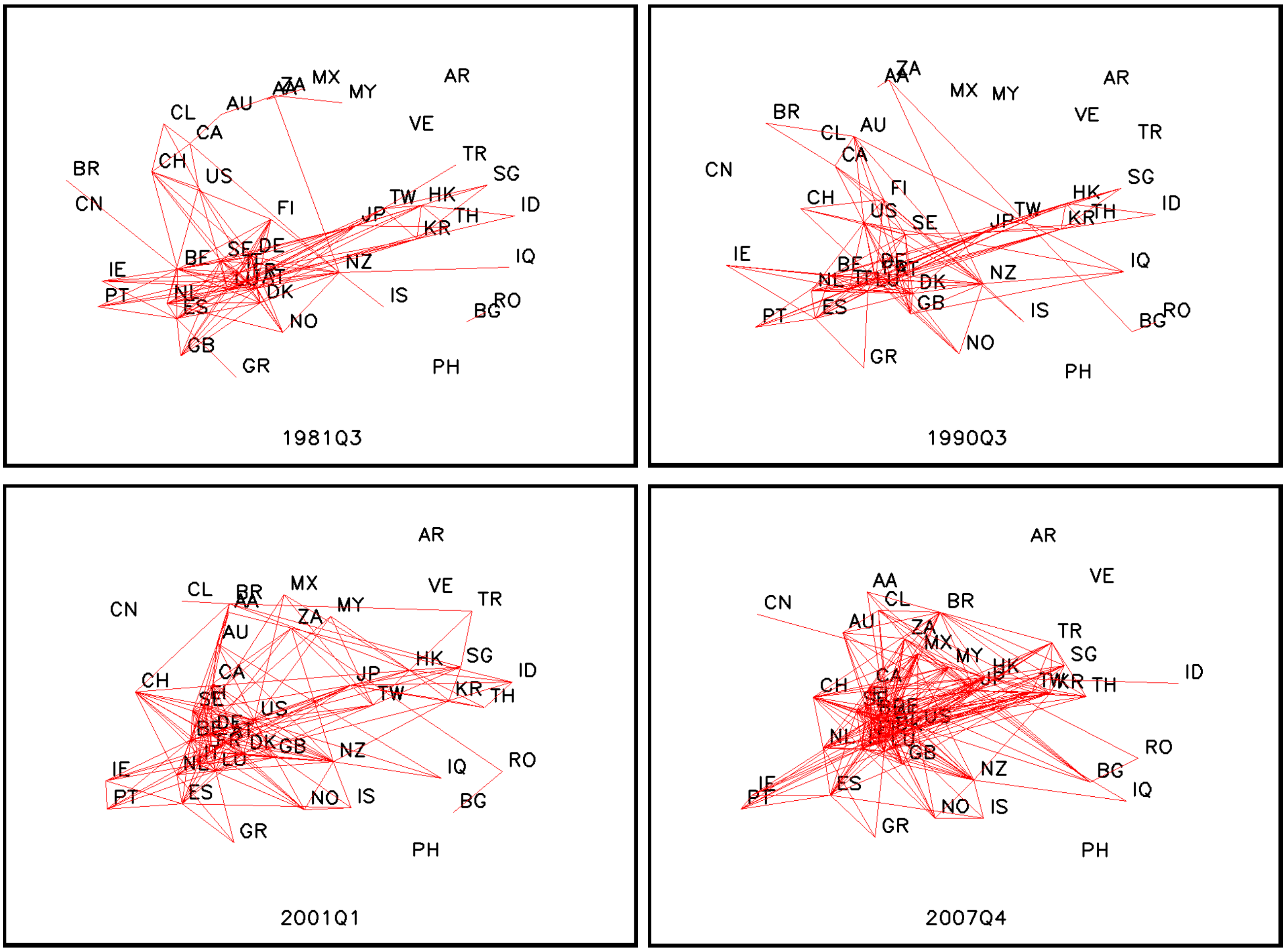


2003-2013



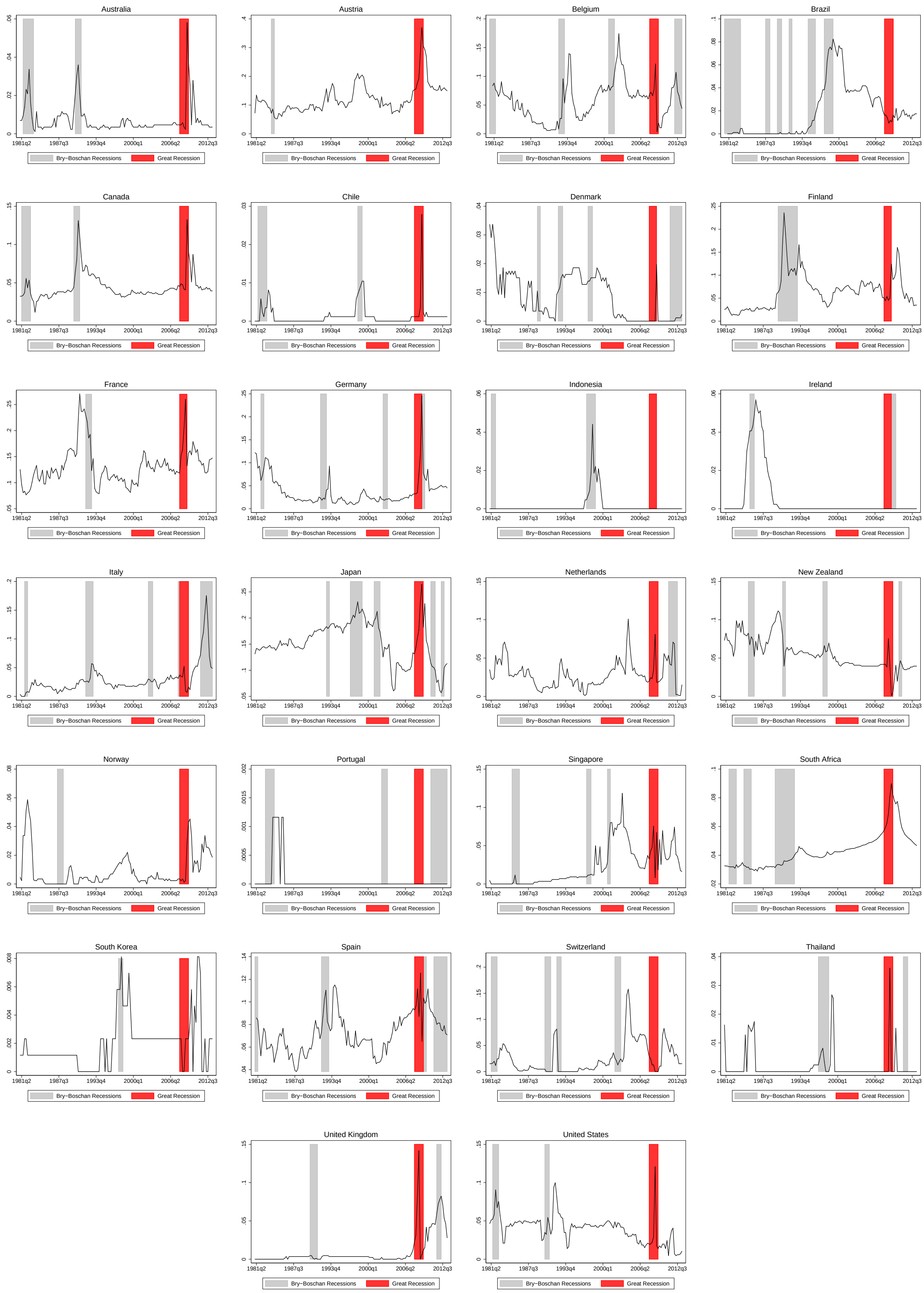
Note: The length of the dendrograms represents the level of dissimilarity at which observations or clusters are merged. Different colors represent different clusters based on a given level of dissimilarity.

Figure 6: World business cycle synchronization network



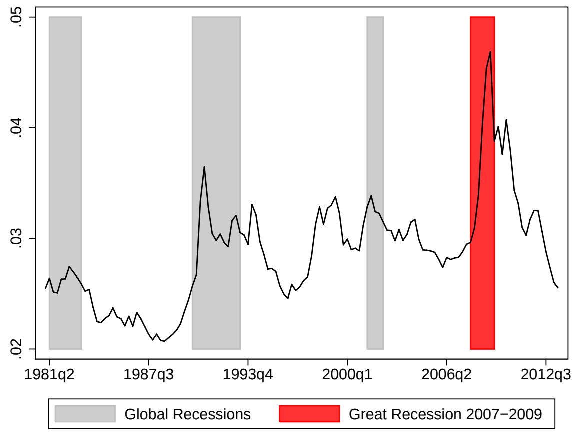
Note: The figure shows dynamic multidimensional scaling maps based on the distance between the business cycles of 43 developed and developing countries across periods of global recessions, as dated by the IMF: 1981 quarter 3, 1990 quarter 3, 2001 quarter 1, and 2007 quarter 4. The closer two countries are in the map, the higher their business cycle synchronization is. Red lines denote links between pairs of countries, which are drawn if the probability that both countries are in a synchronized phase is higher than 0.5. The sequence of maps for the 1981:Q1-2013:Q2 periods can be found at: *https://sites.google.com/site/daniloleivaleon/global-business-cycles*

Figure 7: Betweenness centrality of countries



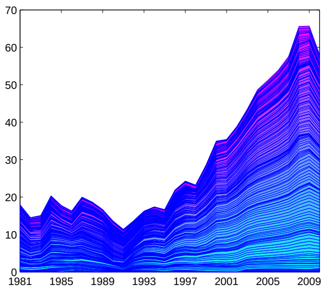
Note: Each chart plots the betweenness centrality for each country in the world business cycle synchronization network. The grey bars denote recessions identified by using the Bry-Boschan algorithm, and the red bar, the Great Recession of 2007-2009.

Figure 8: Average betweenness centrality

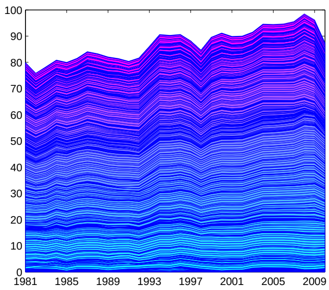


Note: The figure plots the average betweenness centrality across countries. Grey bars denote the 1981-1983, 1990-1993 and 2001-2002 global recessions, as dated by the IMF, and the red area the Great Recession of 2007-2009.

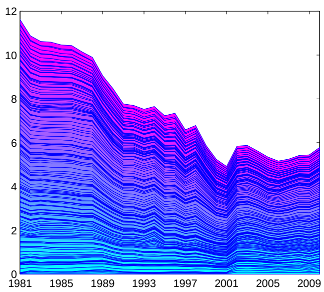
Figure 9: Increasing versus Stable Synchronization in pairs of countries



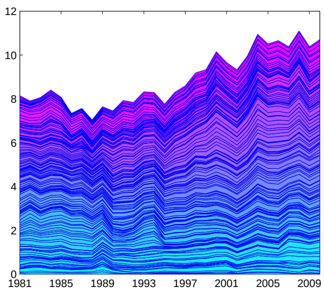
(a) Increasing Synch. group



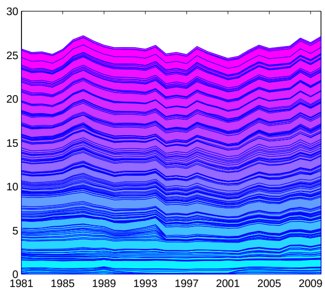
(b) Stable Synch. group



(c) Agriculture



(d) Industry



(e) Service

Note: Charts (a) and (b) show the synchronizations for the two groups of countries identified with the K-Spectral Centroid algorithm. Charts (c), (d) and (e) show the differences in agriculture, industry and services, respectively, as shares of GDP for increasing sync. countries.

Appendix for

Dynamics of Global Business Cycles Interdependence*

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Appendix A: Filtering Algorithm

This appendix shows how to compute the inferences regarding the business cycle states given the model's parameters, collected in θ. The basic states of $y_{ab,t} = [y_{a,t}, y_{b,t}]'$, in Equation (1), can be defined with the state variable

$$s_{ab,t} = \begin{cases} 1 \text{ if } s_{a,t} = 0 \text{ and } s_{b,t} = 0 \\ 2 \text{ if } s_{a,t} = 1 \text{ and } s_{b,t} = 0 \\ 3 \text{ if } s_{a,t} = 0 \text{ and } s_{b,t} = 1 \\ 4 \text{ if } s_{a,t} = 1 \text{ and } s_{b,t} = 1 \end{cases}, \tag{1}$$

which encompasses all the possible combinations. However, when assessing synchronization, it is convenient to define a new state variable, $s^*_{ab,t}$, that characterizes all possible states of the model in equations (1)-(9), i.e., that governs the individual business cycles and their degree of synchronization.[1]

$$s^*_{ab,t} = \begin{cases} 1 \text{ if } s_{a,t} = 0,\ s_{b,t} = 0, \text{ and } v_{ab,t} = 0 \\ 2 \text{ if } s_{a,t} = 1,\ s_{b,t} = 0, \text{ and } v_{ab,t} = 0 \\ 3 \text{ if } s_{a,t} = 0,\ s_{b,t} = 1, \text{ and } v_{ab,t} = 0 \\ 4 \text{ if } s_{a,t} = 1,\ s_{b,t} = 1, \text{ and } v_{ab,t} = 0 \\ 5 \text{ if } s_{a,t} = 0,\ s_{b,t} = 0, \text{ and } v_{ab,t} = 1 \\ 6 \text{ if } s_{a,t} = 1,\ s_{b,t} = 0, \text{ and } v_{ab,t} = 1 \\ 7 \text{ if } s_{a,t} = 0,\ s_{b,t} = 1, \text{ and } v_{ab,t} = 1 \\ 8 \text{ if } s_{a,t} = 1,\ s_{b,t} = 1, \text{ and } v_{ab,t} = 1 \end{cases}. \tag{2}$$

Using an extended version of the procedure described in Hamilton (1989), inferences regarding the business cycle states are calculated as a byproduct of an algorithm based on the iterative application of the following two steps:

STEP 1: *Computing the likelihoods.* At time t, the method adds the observation $y_{ab,t} = (y_{a,t}, y_{b,t})'$ to $\widetilde{y}_{ab,t-1}$ and accepts as the input the forecasting probabilities

$$p\left(s^*_{ab,t} = i^*_{ab} | \widetilde{y}_{ab,t-1}, \theta\right) \tag{3}$$

for $i^*_{ab} = 1, 2, ..., 8$. In this case, the likelihood of $y_{ab,t}$ is

$$f_{ab}\left(y_{ab,t} | \widetilde{y}_{ab,t-1}, \theta\right) = \sum_{i=1}^{8} f_{ab}\left(y_t | s^*_{ab,t} = j^*_{ab}, \widetilde{y}_{ab,t-1}, \theta\right) p\left(s^*_{ab,t} = j^*_{ab} | \widetilde{y}_{ab,t-1}, \theta\right), \tag{4}$$

where $f_{ab}(\bullet)$ is the conditional Gaussian bivariate density function.

To make an inference, the joint probabilities can be obtained from the marginal probabilities as

$$p\left(s^*_{ab,t} = j^*_{ab} | \widetilde{y}_{ab,t-1}, \theta\right) = p\left(s_{ab,t} = j_{ab} | v_{ab,t} = j_v, \widetilde{y}_{ab,t-1}, \theta\right) p\left(v_{ab,t} = j_v | \widetilde{y}_{ab,t-1}, \theta\right), \tag{5}$$

with $j^*_{ab} = 1, ..., 8$, $j_{ab} = 1, ..., 4$ and $j_v = 0, 1$. The way in which the model computes inferences regarding the four-state unobservable variable $s_{ab,t}$ depends on the business cycle synchronization between countries a and b. Suppose that each of these two countries follows independent phase-shifting processes, i.e., $v_{ab,t} = 0$. Then, the four-state probability term of $s_{ab,t}$ is

$$p\left(s_{ab,t} = j_{ab} | v_{ab,t} = 0, \widetilde{y}_{ab,t-1}, \theta\right) = p\left(s_{a,t} = j_a | \widetilde{y}_{ab,t-1}, \theta\right) p\left(s_{b,t} = j_b | \widetilde{y}_{ab,t-1}, \theta\right), \tag{6}$$

with $j_{ab} = 1, ..., 4$. By contrast, if the two countries exhibit perfectly correlated business cycles, which occurs when $v_{ab,t} = 1$, they could be represented by the same state variable since $s_{a,t} = s_{b,t}$. Therefore, one can define a new four-state variable $\varsigma_{ab,t}$ as in (1), where states 2 and

[1] The probabilities of the occurrence of states 6 and 7 are zero by definition.

3 never occur and where the two countries share the cycle in states 1 and 4. In this case, the probability term is

$$p\left(s_{ab,t}=j_{ab}|v_{ab,t}=1,\widetilde{y}_{ab,t-1},\theta\right)=p\left(\varsigma_{ab,t}=j_{ab}|\widetilde{y}_{ab,t-1},\theta\right), \tag{7}$$

with $j_{ab}=1,...,4$ and $p\left(\varsigma_{ab,t}=2|\widetilde{y}_{ab,t-1},\theta\right)=p\left(\varsigma_{ab,t}=3|\widetilde{y}_{ab,t-1},\theta\right)=0$. The transition probabilities of $\varsigma_{ab,t}$ are

$$p\left(\varsigma_{ab,t}=j_{ab}|\varsigma_{ab,t-1}=i_{ab},\varsigma_{ab,t-2}=h_{ab},...,\widetilde{y}_{ab,t-1}\right)=p\left(\varsigma_{ab,t}=j_{ab}|\varsigma_{ab,t-1}=i_{ab}\right)=q_{ij}^{ab}. \tag{8}$$

STEP 2: *Updating the forecasting probabilities.* Using the data up to time t, the optimal inference regarding the state variables can be obtained in the following way:

$$p\left(s_{k,t}=j_k|\widetilde{y}_{ab,t},\theta\right) = f_k\left(y_{k,t}|s_{k,t}=j_k,\widetilde{y}_{ab,t-1},\theta\right)p\left(s_{k,t}=j_k|\widetilde{y}_{ab,t-1},\theta\right)/f_k\left(y_{k,t}|\widetilde{y}_{ab,t-1},\theta\right), \tag{9}$$

$$p\left(v_{ab,t}=j_v|\widetilde{y}_{ab,t},\theta\right) = f_{ab}\left(y_{ab,t}|v_{ab,t}=j_v,\widetilde{y}_{ab,t-1},\theta\right)p\left(v_{ab,t}=j_v|\widetilde{y}_{ab,t-1},\theta\right)/f_{ab}\left(y_{ab,t}|\widetilde{y}_{ab,t-1},\theta\right) \tag{10}$$

$$p\left(\varsigma_{ab,t}=j_{ab}|\widetilde{y}_{ab,t},\theta\right) = f_{ab}\left(y_{ab,t}|\varsigma_{ab,t}=j_{ab},\widetilde{y}_{ab,t-1},\theta\right)p\left(\varsigma_{ab,t}=j_{ab}|\widetilde{y}_{ab,t-1},\theta\right)/f_{ab}\left(y_{ab,t}|\widetilde{y}_{ab,t-1},\theta\right) \tag{11}$$

where $f_k(\bullet)$ is the conditional Gaussian univariate density function of country j_k, $j_v=1,2$, $j_{ab}=1,...,4$, and $k=a,b$.

Finally, one can forecast how likely the processes are in period $t+1$ by using the observations up to date t. These forecasts can be computed by using the following expressions:

$$p\left(s_{k,t+1}=j_k|\widetilde{y}_{ab,t},\theta\right) = \sum_{i_k=0}^{1}p\left(s_{k,t}=i_k|\widetilde{y}_{ab,t},\theta\right)p_{ij}^{k}, \tag{12}$$

$$p\left(v_{ab,t+1}=j_v|\widetilde{y}_{ab,t},\theta\right) = \sum_{i=0}^{1}p\left(v_{ab,t}=i_v|\widetilde{y}_{ab,t},\theta\right)p_{ij}^{ab}, \tag{13}$$

$$p\left(\varsigma_{ab,t+1}=j_{ab}|\widetilde{y}_{ab,t},\theta\right) = \sum_{i=1}^{4}p\left(\varsigma_{ab,t}=i_{ab}|\widetilde{y}_{ab,t},\theta\right)q_{ij}^{ab}. \tag{14}$$

Then, the joint probabilities $p\left(s_{ab,t+1}^{*}=j_{ab}^{*}|\widetilde{y}_{ab,t},\theta\right)$ can be updated by using (5), and they can be used to compute the likelihood for the next period, as described in the first step.

Appendix B: Clustering Analysis

To compute the dendrograms, we begin the analysis with $N(N-1)/2$ clusters, each containing only one country. Using the matrix of business cycle distances, $D=[d_{ij}]$, the algorithm searches for the "most similar" pairs of countries, so that country a and b are selected. In this respect, we follow the most similar criterion that is based on the minimum increase in the within-group variance of distances. Countries a and b are now combined into a new cluster, called p, which reduces the total number of clusters by one. Then, dissimilarities between the new cluster and the remaining clusters are computed again following the most similar criterion. For instance, the distance from the new cluster p to, say, country q, is computed according to

$$d_{p,q}=\frac{n_a+n_q}{n_p+n_q}d_{a,q}+\frac{n_b+n_q}{n_p+n_q}d_{b,q}-\frac{n_q}{n_p+n_q}d_{a,b}, \tag{B1}$$

where n_a, n_b, n_p and n_q are the number of countries included in the respective clusters, and $d_{a,b}$, $d_{a,q}$, and $d_{b,q}$ are the business cycle distances. Finally, these steps are repeated until all countries form a single cluster.

Appendix C: Dynamic Multidimensional Scaling Analysis

Given the matrix of business cycle distances, the technique searches the so-called $(N \times 2)$ configuration matrix that contains the position in two orthogonal axes to which each country is placed in the map. In a recent work, Xu et al. (2012) propose a way to deal with multidimensional scaling in a dynamic fashion, where the dimensional coordinates of the projection of any two objects, i and j, are computed by minimizing the stress function,

$$\min_{\tilde{\gamma}_t^{ij}} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}(\gamma_t^{ij} - \tilde{\gamma}_t^{ij})^2}{\sum_{i,i}(\gamma_t^{ij})^2} + \beta \sum_{i=1}^{n} \tilde{\gamma}_{t|t-1}^{i}, \tag{15}$$

where

$$\begin{aligned} \tilde{\gamma}_t^{ij} &= (||z_{i,t} - z_{j,t}||^2)^{1/2} & (16)\\ \tilde{\gamma}_{t|t-1}^{i} &= (||z_{i,t} - z_{i,t-1}||^2)^{1/2}, & (17) \end{aligned}$$

$z_{i,t}$ and $z_{j,t}$ are the k-dimensional projection of the objects i and j, and β is a temporal regularization parameter that serves to zoom in or zoom out changes between frames at t and at $t+1$, always keeping the same dynamics independent of its value. In principle, β can be simply set up to 1; however, since the data in Γ_t belong to the unit interval, for a more adequate visual perception of the transitions between frames it is set up to 0.1. The output of the minimization in Equation (15) provides a two-dimensional representation of the matrix of business cycle distances.

Appendix D: Variable Definitions

In this appendix we define all the determinants considered in the empirical analysis.

- *Agriculture* value added measures the output of the agricultural sector (ISIC divisions 1-5) less the value of intermediate inputs. Agriculture comprises value added from forestry, hunting, and fishing as well as cultivation of crops and livestock production. Data are in constant 2005 U.S. dollars. Source: World Development Indicator, 2013.

- *Bank Deposits to GDP (%)* The total value of demand, time and saving deposits at domestic deposit money banks as a share of GDP. Deposit money banks comprise commercial banks and other financial institutions that accept transferable deposits, such as demand deposits. Source: Global Financial Development Report, The World Bank, 2013.

- *Deposit money banks' assets to GDP (%).* Total assets held by deposit money banks as a share of GDP. Assets include claims on domestic real non-financial sector which includes central, state and local governments, non-financial public enterprises and private sector. Deposit money banks comprise commercial banks and other financial institutions that accept transferable deposits, such as demand deposits. Source: IMF, Government Finance Statistics, 2013.

- Total Bilateral *Exports* aggregated at national level. Source: IMF, Direction of Trade Statistics, 2013.

- *Financial System Deposits to GDP.* Demand, time and saving deposits in deposit money banks and other financial institutions as a share of GDP calculated using the following deflation method: $(0.5)[F_t/P_{e,t} + F_{t-1}/P_{e,t-1}]/[GDP_t/P_{a,t}]$ where F is demand and time and saving deposits, $P_{e,t}$ is end-of period CPI, and P_a is average annual CPI. Source: Global Financial Development Report, The World Bank, 2013.

- *Gross Domestic Product* at purchaser's prices is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. Data are in current U.S. dollars. Source: World Development Indicator, 2013.

- The *Human capital* index is based on years of schooling (Barro/Lee, 2012) and rates of return for completing different sets of years of education (Psacharopoulos, 1994). Source: Penn World Table 8.0.

- *Industry* value added corresponds to ISIC divisions 10-45 and includes manufacturing (ISIC divisions 15-37). It comprises value added in mining, manufacturing, construction, electricity, water, and gas. Value added is the net output of a sector after adding up all outputs and subtracting intermediate inputs. Data are in current U.S. dollars. Source: World Development Indicator, 2013.

- Total Bilateral *Imports* aggregated at national level. Source: IMF, Direction of Trade Statistics, 2013.

- *Liquid liabilities* are also known as M3. They are the sum of currency and deposits in the central bank (M0), plus transferable deposits and electronic currency (M1), plus time and savings deposits, foreign currency transferable deposits, certificates of deposit, and securities repurchase agreements (M2), plus travelers checks, foreign currency time deposits, commercial paper, and shares of mutual funds or market funds held by residents. Source: Global Financial Development Report, The World Bank, 2013.

- *Population* is the number of people living in the country. Source: Penn World table 8.0.

- *Private Credit Growth* is the growth rate of private credit by deposit money banks and other financial institutions to GDP. Source: Global Financial Development Report, The World Bank, 2013.

- *Private Credit by Deposit Money Bank to GDP* measures the financial resources provided to the private sector by domestic money banks as a share of GDP. Domestic money banks comprise commercial banks and other financial institutions that accept transferable deposits, such as demand deposits. Source: Global Financial Development Report, The World Bank, 2013.

- *Private credit by deposit money banks and other financial institutions to GDP (%).* Source: Global Financial Development Report, The World Bank, 2013.

- *Service* includes value added in wholesale and retail trade (including hotels and restaurants), transport, and government, financial, professional, and personal services such as education, health care, and real estate services'. Source: World Development Indicator, 2013.

- *Urban Population* refers to people living in urban areas as defined by national statistical offices. It is calculated using World Bank population estimates and urban ratios from the United Nations World Urbanization Prospects. Source: World Development Indicator, 2013.

Appendix E: Tables of Robustness Section

This Appendix reports the tables for the robustness analysis in Section 3.4.

Table I: Determinants of business cycle de-synchronization before and after the break: A BMA approach. UIP prior. Static panel

PIP Before the Break (period: 1983-)	2000	2001	2002	2003	2004
Financial Openness	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Government Expenditure(% of GDP)	**0.8872**	**0.9943**	**0.9942**	**0.9974**	**0.9916**
Bilateral Trade	0.7219	**0.9610**	0.7756	0.5039	0.6252
Liquid Liabilities to GDP diff.	0.2555	0.6317	0.2189	0.4031	0.4027
Human Capital index diff.	**0.9583**	0.6070	0.5915	0.5015	0.5320
Difference of sectoral composition	0.0451	0.0873	0.0313	0.0242	0.0454
Private Credit to GDP diff.	0.0158	0.0460	0.0433	0.0530	0.0309
Capital Stock per capita diff.	0.0688	0.0321	0.0231	0.0147	0.0949
Financial System Deposit to GDP diff.	0.0174	0.0288	0.0102	0.0100	0.0106
Urban population diff. (% of total population)	0.0126	0.0146	0.0097	0.0088	0.0091
PIP After the Break (period: -2010)	2001	2002	2003	2004	2005
Financial Openness	0.2060	0.2533	0.2808	0.2199	0.4563
Government Expenditure(% of GDP)	0.1423	0.1794	0.1674	0.2097	0.3641
Bilateral Trade	0.1271	0.0799	0.1717	0.1220	0.2107
Liquid Liabilities to GDP diff.	0.0857	0.0799	0.4636	0.2205	0.2756
Human Capital index diff.	0.0319	0.4010	**0.8383**	0.6638	0.5730
Difference of sectoral composition	**0.9707**	**0.9990**	**0.9989**	**1.0000**	**1.0000**
Private Credit to GDP diff.	0.0107	0.0800	0.1964	0.1261	0.4020
Capital Stock per capita diff.	0.1163	0.0806	0.1874	0.1297	0.2155
Financial System Deposit to GDP diff.	0.1065	0.0803	0.2318	0.4300	**0.8122**
Urban population diff. (% of total population)	0.2365	0.1176	0.2408	0.1585	0.2272

The sample period considered before the break is from 1983 to the year specified in the selected column. After the break, the sample considered is from the year specified in the selected column to 2010. The results are obtained by using 30 developed and developing countries. The dependent variable is distance or de-synchronization of the business cycles of two countries. Most of the regressors capture differences between the countries, except bilateral trade and financial openness. The results are obtained by using a hierarchical prior model and hyper-g-prior. Entries higher than 0.8 are presented in bold.

Table II: Determinants of business cycle de-synchronization before and after the break: A BMA approach. UIP prior. Dynamic panel

PIP Before the Break (period: 1983-)	2000	2001	2002	2003	2004
De-synchronization$_{t-1}$	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
De-synchronization$_{t-2}$	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Financial Openness	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Government Expenditure(% of GDP)	**0.9996**	**0.9990**	**0.9996**	**0.9979**	**0.9986**
Bilateral Trade	**0.9360**	0.7237	0.3104	0.4559	0.5974
Liquid Liabilities to GDP diff.	0.6672	0.3173	0.7220	0.6964	0.8094
Human Capital index diff.	0.3022	0.4222	0.2816	0.3338	0.4167
Difference of sectoral composition	0.1349	0.0740	0.0644	0.0242	0.3405
Private Credit to GDP diff.	0.0236	0.0243	0.0326	0.0225	0.0196
Capital Stock per capita diff.	0.0314	0.0395	0.0201	0.1387	0.1586
Financial System Deposit to GDP diff.	0.0220	0.0172	0.0152	0.0163	0.0184
Urban population diff. (% of total population)	0.0189	0.0133	0.0122	0.0133	0.0155
PIP After the Break (period: -2010)	2001	2002	2003	2004	2005
De-synchronization$_{t-1}$	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
De-synchronization$_{t-2}$	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Financial Openness	0.0145	0.0126	0.0156	0.0177	0.0304
Government Expenditure(% of GDP)	0.0110	0.0125	0.0085	0.0174	0.0283
Bilateral Trade	0.0089	0.0074	0.0089	0.0089	0.0106
Liquid Liabilities to GDP diff.	0.0135	0.0074	0.0528	0.0301	0.0424
Human Capital index diff.	0.1435	0.0678	0.2739	0.1740	0.0938
Difference of sectoral composition	**0.9570**	**0.9932**	**0.9879**	**1.0000**	**1.0000**
Private Credit to GDP diff.	0.0114	0.0074	0.1964	0.0096	0.0409
Capital Stock per capita diff.	0.0080	0.0075	0.0099	0.0096	0.0111
Financial System Deposit to GDP diff.	0.0072	0.0075	0.0206	0.0835	0.4104
Urban population diff. (% of total population)	0.0174	0.0104	0.0127	0.0112	0.0114

The sample period considered before the break is from 1983 to the year specified in the selected column. After the break, the sample considered is from the year specified in the selected column to 2010. The results are obtained by using 30 developed and developing countries. The dependent variable is distance or de-synchronization of the business cycles of two countries. Most of the regressors capture differences between the countries, except bilateral trade and financial openness. The results are obtained by using a hierarchical prior model and hyper-g-prior. Entries higher than 0.8 are presented in bold.

Table III: Determinants of business cycle de-synchronization before and after the break: A Weighted Average Least Squares approach. Static panel.

t-statistic Before the Break (period: 1983-)	2000	2001	2002	2003	2004
Financial Openness	**5.84**	**5.32**	**5.36**	**5.63**	**6.15**
Government Expenditure(% of GDP)	**4.73**	**4.76**	**4.65**	**4.85**	**5.14**
Bilateral Trade	**-3.46**	**-3.15**	**-3.11**	**-3.33**	**-3.84**
Liquid Liabilities to GDP diff.	-1.98	**-2.13**	**-2.01**	**-2.05**	**-2.15**
Human Capital index diff.	**3.24**	**3.70**	**3.61**	**3.71**	**4.04**
Difference of sectoral composition	**-2.25**	-1.90	**-2.10**	**-2.52**	**-2.71**
Private Credit to GDP diff.	1.67	1.64	1.35	1.07	1.26
Capital Stock per capita diff.	-1.32	-1.43	**-2.37**	**-2.60**	**-2.89**
Financial System Deposit to GDP diff.	-0.39	-0.38	-0.19	-0.20	-0.26
Urban population diff. (% of total population)	0.29	0.61	0.65	0.59	0.37
t-statistic After the Break (period: -2010)	2001	2002	2003	2004	2005
Financial Openness	-1.28	-1.30	-1.73	**-2.11**	**-2.28**
Government Expenditure(% of GDP)	0.42	-0.22	0.64	1.18	1.06
Bilateral Trade	-0.05	-0.35	-0.03	0.15	0.33
Liquid Liabilities to GDP diff.	1.14	1.68	0.95	1.11	1.19
Human Capital index diff.	**2.04**	**2.15**	**2.18**	1.83	1.22
Difference of sectoral composition	**3.25**	**3.18**	**4.23**	**5.52**	**5.75**
Private Credit to GDP diff.	0.09	-0.43	0.08	1.21	0.74
Capital Stock per capita diff.	-0.47	-0.84	0.07	0.23	0.40
Financial System Deposit to GDP diff.	-0.04	0.31	1.11	1.61	1.73
Urban population diff. (% of total population)	-1.35	-0.83	-0.36	-0.37	-0.45

The results are obtained by using the Weighted Average Least Squares approach introduced by Magnus, Powell, and Prufer (2010). Determinants with a t-statistics larger than 2 are considered robust. The dependent variable is distance or de-synchronization of the business cycles of two countries. Most of the regressors capture divergence between the countries, except bilateral trade and financial openness.

Table IV: Determinants of business cycle de-synchronization before and after the break: A Weighted Average Least Squares approach. Dynamic panel.

t-statistic Before the Break (period: 1983-)	2000	2001	2002	2003	2004
De-synchronization$_{t-1}$	**12.38**	**14.61**	**14.41**	**15.50**	**16.15**
De-synchronization$_{t-2}$	**-17.11**	**-15.66**	**-15.60**	**-16.39**	**-17.04**
Financial Openness	**6.03**	**5.76**	**5.42**	**5.71**	**5.80**
Government Expenditure(% of GDP)	**4.48**	**4.78**	**4.27**	**4.25**	**4.24**
Bilateral Trade	**-3.14**	-1.88	**-2.41**	**-2.76**	**-3.08**
Liquid Liabilities to GDP diff.	**-2.22**	**-2.77**	**-2.70**	**-2.67**	**-2.83**
Human Capital index diff.	**3.28**	**2.79**	**3.28**	**3.17**	**3.35**
Difference of sectoral composition	-1.81	-1.85	**-2.02**	**-2.64**	**-2.94**
Private Credit to GDP diff.	1.94	**2.04**	1.65	1.27	1.52
Capital Stock per capita diff.	-1.82	-1.58	**-2.20**	-1.89	-1.85
Financial System Deposit to GDP diff.	-0.43	-0.55	-0.41	-0.44	-0.40
Urban population diff. (% of total population)	0.11	-0.21	-0.14	-0.40	-0.40
t-statistic After the Break (period: -2010)	2001	2002	2003	2004	2005
De-synchronization$_{t-1}$	**13.63**	**10.21**	**12.11**	**9.16**	**7.95**
De-synchronization$_{t-2}$	**-5.62**	**-7.71**	**-8.57**	**-6.89**	**-5.29**
Financial Openness	-1.24	-0.99	-1.19	-1.90	-1.98
Government Expenditure(% of GDP)	1.56	0.34	1.37	1.11	1.32
Bilateral Trade	0.48	0.15	0.35	0.21	0.20
Liquid Liabilities to GDP diff.	0.09	1.39	0.35	0.40	0.75
Human Capital index diff.	**2.41**	**3.14**	**2.25**	2.03	0.81
Difference of sectoral composition	**3.43**	**3.17**	**4.19**	**4.86**	**5.20**
Private Credit to GDP diff.	0.26	-0.42	0.59	1.84	0.87
Capital Stock per capita diff.	-0.13	-0.66	0.19	-0.04	0.25
Financial System Deposit to GDP diff.	-0.25	0.33	0.98	1.49	1.72
Urban population diff. (% of total population)	-1.55	-0.97	-0.81	-0.66	0.01

The results are obtained by using the Weighted Average Least Squares approach introduced by Magnus, Powell, and Prufer (2010). Determinants with a t-statistics larger than 2 are considered robust. The dependent variable is distance or de-synchronization of the business cycles of two countries. Most of the regressors capture divergence between the countries, except bilateral trade and financial openness.