Global Business Cycles Interdependence: Dynamics and Determinants*

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Abstract

In this paper, we examine the time-varying interdependence among the business cycles of the major world economies and assess the main drivers of this interdependence. We provide a comprehensive analysis of the propagation of business cycle shocks among developed and developing countries from synchronization, clustering, and network perspectives. We then evaluate the ability of several potential factors to explain business cycle interdependence by using a bayesian model averaging approach to account for model uncertainty. The results document a structural increase in global business cycle interdependence in the early 2000s and four clusters of countries that are relatively stable over time: the Euro area, the Asian tigers, the Anglo-Saxon, and the emerging markets clusters. We also find that the most robust determinants of business cycle interdependence tend to be financial openness, specialization, bilateral trade, inflation, consumption share, and human capital. However, these determinants vary across time.

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1 Introduction

Recent decades have witnessed increased globalization of the world economy and 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. Therefore, understanding the patterns and mechanisms governing world economic interdependence is crucial for policy makers to able to evaluate the probability of recessions based on business cycle co-movement and to formulate policies to mitigate the transmission of negative shocks among countries.

The literature on the determinants of business cycle synchronization has increased in recent years. Before 2009, most of the studies in the literature stream 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 the main determinants of business cycle synchronization. Traditional determinants that are considered in the empirical literature on business cycle synchronization include trade intensity, common sectoral composition, and financial integration. Frankel and Rose (1998) find a positive relationship between trade and business cycle synchronization. Imbs (2004) simultaneously estimates the effect of trade, financial integration, and specialization on business cycle synchronization and finds positive effects of financial integration and trade on business cycle synchronization. He also finds a negative relationship between similar economic structure (sectoral composition) and business cycle synchronization. Trade also affects positively specialization, but this effect is dominated by the positive relationship between trade intensity and business cycle synchronization.[1] In addition to the traditional determinants, Rose and Engel (2002) incorporate currency union as a potential factor driving business cycle co-movement. Baxter and Kouparitsas (2005) study the role of similarities in export and import baskets and sectoral structure and find that these factors are not robust determinants of business cycle synchronization. Kose et al. (2003) find that globalization does not explain variation in business cycle co-movement across countries.

[1]The exogenous variation of financial integration is exploited by using creditor rights, shareholder rights indices, and enforcement laws, while trade intensity is instrumented by using 'gravity variables, such as distance between the capital of the examined two countries and common border dummies.

Camacho et al. (2008) consider three different measures of business cycle synchronization based on VAR estimation, spectral analysis, and business cycle dummy variables and find that similarities in sector composition, trade, and public sector size explain variation in business cycle synchronization across countries. Imbs (2006) and Clark and van Wincoop (2001) find high synchronization between financially open developing countries and the Group of Seven (G7): Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States. In recent studies, Canova and Ciccarelli (2012) and Canova and Schlaepfer (2013) analyze business cycle interdependence among Mediterranean countries and find that traditional transmission channels, trade, and financial integration are not very important determinants of business cycle interdependence in this region. Altug and Canova (2012) examine the business cycles of 45 countries and find that similarities in the institutional environment and cultural factors are related to business cycle interdependence.

Although these studies contribute to a better understanding of the factors influencing business cycle synchronization, they have two important limitations. First, these studies focus on a time-invariant measure of synchronization and do not account for potential changes in synchronization patterns caused by trade agreements, economic unions, and financial liberalization, among other events. Notice that, if synchronization patterns and potential determinants of synchronization do experience significant variation over time, a cross-sectional regression analysis may yield misleading insights about the main factors driving business cycle synchronization. Second, 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 considerably 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.

In a recent study, Cerqueira and Martins (2009) address the first drawback by introducing a time-varying synchronization index based on the dynamic correlation of the GDP growth rates between two countries and use panel data models to estimate the role of trade, financial openness, and specialization in business cycle synchronization.[2] Artis and Okubo (2011) use the measure of Cerqueira and Martins (2009) to re-evaluate the relationship between trade

[2]Del Negro and Otrok (2008) use a dynamic factor model with time-varying factor loadings and stochastic volatility to study the evolution of international business cycles for nineteen countries.

and business cycle synchronization in a panel setting. They find a positive effect of trade on business cycle co-movement during the current globalization period but a negative effect during the interwar period. Jean-Louis and Simons (2014) study the dynamics of business cycle synchronization in high-income economies, middle-income economies, and low-income economies. Their results suggest that high-income economies are more synchronized than middle-income economies and low-income countries.[3] Kalemli-Ozcan et al. (2013a) analyze the effect of financial globalization, measured as bilateral stocks of assets and liabilities, on bilateral business cycle synchronization, measured as the difference in log GDPs. Although the synchronization index proposed in Cerqueira and Martins (2009) allows a time dimension to be incorporated into an analysis, this index is not without shortcomings. First, the index relies on the difference in the GDP growth between two countries. Therefore, it does not account for the asymmetry inherent to business cycle phases, which is usually captured by using non-linear dynamic models, e.g., Markov-switching models. Second, although the index is constructed based on the notion of correlations, it is an unbounded measure that may also take extreme negative values for some periods, making its interpretation ambiguous.

In this paper, we contribute to the existing literature by providing a comprehensive analysis of the main determinants of business cycle interdependence that accounts for both shortcomings present in the previous works, dynamic non-linear synchronization patterns and model uncertainty. Specifically, we consider the time-varying index for business cycle interdependence recently proposed by Leiva-Leon (2014). This index endogenously captures the non-linearity inherent to the alternation between expansions and recessions. It allows us to study the co-movement of business cycle phases over time and to evaluate the main determinants of such co-movement. We rely on a Bayesian Model Averaging (BMA) approach, as in the empirical economic growth literature (Sala i Martin et al. (2004), Moral-Benito (2012), Cuaresma et al. (2014), among others), to account for model uncertainty in identifying the main determinants of business cycle interdependence in the short and long run. The proposed analysis allows us to address the following questions: How has global business cycle interdependence evolved since the Great Moderation? Are clusters of countries experiencing similar cyclical patterns? Is global synchronization useful for anticipating country-specific recessions? What are the main factors driving business cycle interdependence in the short and long run?

Our main results can be summarized as follows. First, we document a structural change in world business cycle synchronization. Specifically, global interdependence has significantly

[3]The authors also find that trade openness and shocks to consumption are not robust determinants of business cycle synchronization but rather are determinants of shocks to oil prices.

increased during the recent globalization period, since the early 2000s.[4] 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: a 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 due to such economies have become more synchronized with the rest of the world since the 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 results suggest that the most robust determinants of business cycle co-movement are financial openness, bilateral trade, inflation, consumption share, and human capital. We also find that these determinants vary across time and across clusters.[5]

In what follows, we first introduce and discuss the index of synchronization in section 2. In section 3, we study the main determinants of business cycle interdependence in the short and long run. Section 4 presents a robustness analysis of the main results of the paper, and section 5 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 studies, we rely on measures of synchronization that allow for non-linear dynamics inherent in expansionary and recessionary phases. First, we construct 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 side. 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

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

[5]Leiva-Leon (2014) also finds that similar results hold also at the regional level, for the states of U.S.

cycles between pair of countries over time, taking into account the asymmetric nature of business cycles, i.e., non-linear dynamics.[6] 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:

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

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

[6] 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).

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 (1994) 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.[7] 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 sync 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:

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

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.[8]

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 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.

[7]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.

[8]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.

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.[9] 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 plot 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.

2.2 Assessing the Increase in Synchronization

The purpose of this section is to assess the main source of the increase in global synchronization from the country side. 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 are able to address 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 main contributors to the increase in global interdependence.

[9]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.

2.2.1 Groups of Countries

We use an agglomerative hierarchical cluster tree (Ward's 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.[10] 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 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

[10] 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.

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.

Next, we proceed to 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.

Figure 6 shows the real GDP growth of the countries specified in Table 1 grouped by cluster; the vertical dashed line in the figure captures the break point in 2002. The figure shows a significant increase in co-movement among countries in each group since the end of 2002. The largest increase is found for the Euro area and emerging markets clusters, followed by the Asian Tigers cluster and the Anglo-Saxon cluster, which experienced the most co-movement for the entire sample period. In section 3, we study the possible factors driving the increase in global synchronization across clusters.

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 assess: where is the increase in global business cycle interdependence 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 7 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 7), 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. [11]

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

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

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 the concept of recession is usually associated with 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 attempt to mitigate this caveat 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 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

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

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. [12]

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 8, 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 9 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.

3 Drivers of Business Cycles Interdependence

There is no well-defined agreement in the literature about the main determinants of business cycle synchronization. The results differ substantially depending on the data, methodology, and variables considered. There are also different theories suggesting different potential deter-

[12] 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.

minants of business cycle synchronization. In this section, we identify the main determinants of business cycle interdependence by using a BMA approach to account for model uncertainty. The analysis is performed from two perspectives. First, we study the determinants by using the within-variation across time and the between-variation across countries (i.e., using panel data regressions) to identify what we call "cyclical" determinants, which explain changes in business cycle interdependence, such as the global increase in business cycle interdependence in the early 2000s. Second, we focus only on the cross-sectional dimension to assess what we define as "persistent" determinants, which explain the long-run pattern of business cycle interdependence and the clustering patterns across countries.[13] 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 and across countries.

3.1 Data

3.1.1 Cyclical Determinants

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: bilateral trade, specialization, and financial openness. In addition to these standard potential determinants, we include in our panel data analysis private and public consumption, demographic factors, macroeconomic indicators, and several financial factors. In the panel data analysis, 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.[14] We consider the following factors as potential determinants:

- **Economic** factors: factors: bilateral trade, exchange rate, foreign direct investment share (i.e., as a percentage of GDP), consumption share, investment share, government expenditure share, differences in sectoral composition, inflation rate, human capital index, and gross capital formation. 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,

[13]The cross-sectional analysis also allows us to mitigate some of the data constraints detailed below.

[14]Definitions for all the variables are provided in Appendix C.

2006).[15] This trade channel is captured in our analysis by including bilateral trade, which measures the trade volume between two countries, and exchange rate, which accounts for changes in the cost of trading between two economies. Foreign direct investment (FDI) is included as a potential determinant in our analysis because it may increase business cycle synchronization, since vertical FDI will create supply chains across countries by linking the production decisions between a parent company and its affiliates (Jansen and Stokman, 2011).[16] For example, if the parent company reduces production, affiliates located in other countries will also cut the production of intermediate goods, decreasing output in all these countries and consequently increasing business cycle interdependence.

Private consumption, particularly spending on durable goods, decreases during recessions (King and Rebelo, 1999). Investment is also procyclical. However, considerable heterogeneity exists in the composition of aggregate demand across countries, which may also vary over time.[17] To explore whether similarities in the composition of aggregate demand between countries help explain their business cycle synchronization, we include countries' consumption, investment, and government spending shares as potential factors.

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).

Inflation rates in industrialized countries are largely a global phenomenon (Ciccarelli and Mojon, 2010); therefore, their co-movement may also help explain global business cycle synchronization.

Human capital proxies for skilled and unskilled labor and for different levels of economic development. 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

[15]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.

[16]Vertical FDI occurs when firms locate different stages of production in different countries, while horizontal FDI occurs when firms perform the same activity across plants located in other countries.

[17]For example, according to the World Bank, on the one hand, U.S. consumption as share of GDP has remained stable at about 70 percent since the 1980s, but China's consumption share has fallen from 50 percent in 1980 to 35 percent in 2008. On the other hand, the consumption share in Hong Kong and Japan has remained relatively stable, both at approximately 55 percent.

similarities in human capital indexes between two countries to be associated with higher business cycle co-movement. The human capital index, consumption share, government expenditure share, and investment share are taken from the Penn World Table 8.0. The rest of the variables, except bilateral trade, are taken from the World Development Indicators.

- **Financial** factors: financial openness, private credit issued by deposit money banks and other financial institutions to GDP, financial system deposits to GDP, liquid liabilities to GDP, and deposit money bank assets to GDP.

  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).

- **Demographic** factor: Urban population. The proportion of a country's population living in urban areas is highly correlated with its level of income (Bloom et al., 2008). We use urban population to capture different levels of economic development since the empirical evidence suggest that business cycles are more synchronized among developed countries.

We aim to explain de-synchronization among countries, $\gamma_t^{a,b}$, as defined in Equation (12); therefore, we transform our variables to capture dissimilarities between two countries, a and b, for each potential determinant, $x_{ij,t}$. In particular, we compute the absolute value of the difference in factor X between country a and country b.

$$x_{ab,t} = |x_{a,t} - x_{b,t}|. \tag{15}$$

This transformation is applied to all the determinants except bilateral trade, differences in sectoral composition, and financial openness.[18]

[18]We take the log of the human capital index and exchange rate before computing the absolute difference. The rest of the variables are expressed in percentages; thus, we use the direct differences.

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):

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

where $s_{a,t}^{k}$ 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).[19]

Bilateral trade intensity is computed by using the measure in Frankel and Rose (1998),

$$T_{ab,t} = \frac{E_{a,b,t} + I_{a,b,t}}{GDP_{a,t} + GDP_{b,t}} \tag{17}$$

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.[20]

As a measure of financial openness, we use

$$F_{ab,t} = \frac{A_{a,t} + L_{a,t}}{GDP_{a,t}} + \frac{A_{b,t} + L_{b,t}}{GDP_{b,t}} \tag{18}$$

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

3.1.2 Persistent Determinants

To analyze the long-run pattern of business cycle synchronization, we enlarge our set of potential factors by including social, cultural and political determinants.[21]

- **Economic** factors: total factor productivity, international debt issues to GDP, private credit growth, deposits, unemployment, bank credit to GDP, tax revenue, competition index, and the Gini index.
- **Financial** factors: return on assets, credit to government, and stock market total value traded to GDP.
- **Demographic** factors: fertility rate, population, and infant mortality.

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

[20] 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.

[21] Some of these factors considered in the long-run analysis are time varying. However, they could not be used in the short-run analysis, as they were not available for every year.

- **Social** factors: civil liberties, economic freedom world index, economic globalization, gender inequality index, human development index, environmental performance index, social globalization index, and internet users.

- **Cultural** factors: religion fractionalization, linguistic fractionalization, and ethnic fractionalization.

- **Political** factors: government budget, corruption perception index, political constraints index, political stability index, government fractionalization index, political globalization index, and largest government party orientation.

In the long-run analysis, we aim to identify the most robust determinants of the ergodic business cycle synchronization. Hence, we focus on the cross-sectional dimension by averaging all the potential determinants across time.[22]

3.2 Short-Run Analysis

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

$$\gamma_{ab,t} = x_{ab,t}^{'k}\beta^k + \eta_{ab} + \mu_t + v_{ab,t}, \tag{19}$$

where $\gamma_{ab,t}$ is the distance or de-synchronization between the business cycle of countries a and b, and $x_{ab,t}^{'k}$ includes a set of potential determinants. 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.[23] 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, financial deposit to GDP, private credit to GDP, exchange rate, 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.

[22]This approach is popular in the empirical economic growth literature for studying the long-run determinants of economic growth.

[23]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.

The key questions are as follows: Which variables $x'^{k}_{ab,t}$ should be incorporated into the model? What is the expected effect of each of them? 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 $P(M_j|y)$, is defined as

$$P(M_j|y) = \frac{P(y|M_j)P(M_j)}{\sum_{i=1}^{2^k} P(y|M_i)P(M_i)}, \tag{20}$$

where $P(y|M_j)$ is the marginal likelihood of Model j 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.[24]

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

$$P(\theta_h \neq 0|y) = \sum_{\theta_h \neq 0} P(M_k|y), \tag{21}$$

where θ_h contains the coefficients of the regressor set that defines model h according to equation (19). The posterior inclusion probability is interpreted as the probability that a particular variable h belongs to the true pairwise business cycle de-synchronization model.

The posterior mean of $theta_h$ (i.e., the weighted average of the coefficient θ_h) is given by,

$$E(\theta_h|y) = \sum_{j=1}^{2^k} P(M_j|y)E(\theta_h|y, M_j), \tag{22}$$

and its posterior variance is defined as,

$$V(\theta_h|y) = \sum_{j=1}^{2^k} P(M_j|y)V(\theta_h|y, M_j) + \sum_{j=1}^{2^k} P(M_j|y)\left(E(\theta_h|y, M_j) - E(\theta_h|y)\right)^2. \tag{23}$$

Note that the posterior variance includes the weighted average of the estimated variances in each model and the weighted average of the estimates of θ's across all the candidate models.

Because of data limitations regarding the factors described in section 3.1.1, we restrict our analysis to a smaller set of countries. Table 3 reports the main determinants of business cycle

[24]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.

de-synchronization obtained by using the BMA panel approach over the 1981-2010 period for 30 developed and developing countries.[25] Column (1) presents the posterior inclusion probability of each potential time-varying determinant of business cycle de-synchronization. We find that the most robust determinants are differences in consumption share between the two countries, differences in inflation rates between the two countries, financial openness, differences in human capital indexes between the two countries, and bilateral trade. Although we cannot claim any causal relationship between these determinants and business cycle de-synchronization, because of simultaneity bias and reverse causality, we find that all these determinants affect business cycle de-synchronization with the expected sign. The following results are particularly notable:

- Differences in private consumption shares between two countries increase business cycle de-synchronization. This result implies that similarities in the composition of the aggregate demand between countries constitute a key factor explaining business cycle co-movement, particularly the consumption component, which tends to be relatively high in advanced economies.

- Differences in the rates of inflation between two countries increase business cycle de-synchronization. Common inflation rates between two countries could capture common international monetary policy actions. For example, if the central banks of countries a and b target inflation, their inflation rates would tend to be similar, increasing the probability that they are in the same business cycle phase.

- Financial integration has a positive effect on business cycle de-synchronization. This result is consistent with the recent empirical findings by Kalemli-Ozcan et al. (2013a) showing that cross-border banking integration between two countries is negatively related to co-movement of output. Negative shocks to the real sector of one economy decrease bank lending in the affected countries and increase lending in the unaffected economies, increasing the divergence in business cycles between affected and unaffected countries. This result suggests that during our period of analysis, negative shocks to firm productivity dominate shocks to the banking sector, which is plausible since a major banking crisis occurred during the last few years of our sample, from 2007 to 2009.

[25]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.

- Differences in human capital indexes are associated with higher business cycle de-synchronization. Our human capital indexes mainly measure the number of enrolments in high school and tertiary education. In periods of expansion, individuals tend to substitute human capital investment with other economic activities because of the higher opportunity costs of schooling. Therefore, countries with different levels of schooling are more likely to be in different business cycle phases. Human capital can also capture different level of economic development.

- Higher trade intensity decreases business cycle de-synchronization. This result is consistent with previous studies in the literature showing that bilateral trade transmits shocks and synchronizes economies across borders (Imbs (2004), Baxter and Kouparitsas (2005), among many others).

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.[26] The results show that the main determinants of business cycle interdependence are robust to the inclusion of a lagged dependent variable. The only exception is bilateral trade, which has a lower posterior inclusion probability, 0.67.

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. This finding motivated us to split the sample into two periods to determine whether the main determinants of business cycle interdependence changed after the break. Since the exact timing of the break is unclear, in Table 5, we report the results of the BMA panel analysis for different partitions of the sample, i.e., assuming that the break occurred in 1999, 2000, 2001, or 2002. The results are robust to the partition, showing that the determinants found in the analysis before the break are very similar to those obtained by using the full sample period (1981-2010): financial openness, inflation, bilateral trade, human capital, consumption share, and liquidity.

However, we find that after the break, i.e., during the recent globalization era, the most 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

[26]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.

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. To a lesser extent, human capital, investment share, and exchange rate also seem to be significant determinants of business cycle interdependence.

3.3 Long-Run Analysis

Most of previous empirical studies focus on explaining a time-invariant measure of business cycle synchronization by averaging the potential determinants across time. In this section, we compare our results with previous studies in the literature by explaining the ergodic business cycle de-synchronization between countries a and b, γ_{ab}, with a set of potential determinants, averaged over time. The time-invariant de-synchronization is computed with the transition probabilities of the latent variable, v_t, that measures synchronization, which are presented in section 2.1. Specifically, the ergodic business cycle de-synchronization is defined as

$$\gamma_{ab} = \frac{(1 - q_{00}^{ab})}{(2 - q_{00}^{ab} - q_{11}^{ab})}. \tag{24}$$

where q_{00}^{ab} is the estimated transition probability associated with the state variable v_t that measures synchronization, $p\left(v_{ab,t} = 0 | v_{ab,t-1} = 0\right)$. Similarly, q_{11}^{ab} is given by $p\left(v_{ab,t} = 1 | v_{ab,t-1} = 1\right)$.

First, to facilitate comparison with the findings in section 3.2, we report results for an analysis using the same determinants as those used in the short-run analysis. Then, we consider a wider set of potential determinants, described in section 3.1.2, which includes cultural, demographic, and political factors.

Table 6 reports the results of the BMA approach using ergodic de-synchronization as the dependent variable and the time-averaged potential determinants described in section 3.1.2 as regressors. The results show that the most robust long-run determinants ("persistent" determinants) are differences in urban population between the countries, financial openness, differences in gross capital formation between the countries, and bilateral trade.[27] The results confirm the importance of financial openness and bilateral trade in explaining business cycle co-movement in the short and long run. We also find a positive relation between differences in urban population, which are highly correlated with differences in the level of economic development, and business cycle de-synchronization. This result is consistent with the findings presented in the clustering analysis, as shown in Figure 5, where we observe groups of developed economies (the

[27] Differences in liquid liabilities to GDP also have a high probability of inclusion; however, its associated coefficient is not significant at conventional levels.

Euro area and Anglo-Saxon clusters) and developing countries (he Asian Tigers and emerging markets clusters). This clustering pattern between developed and developing countries suggests that the level of economic development is an important factor explaining "persistent" business cycle interdependence. Although the investment share of an economy does not seem to be a key determinant in the short run, similarities in the gross capital formation between two countries constitute a significant factor explaining their long-run or ergodic business cycle interdependence. Further, similarities in gross capital formation are associated with higher business cycle co-movement.

In the short-run analysis, we adopt a BMA panel approach, so we have to restrict our analysis to determinants that are available for the whole sample period (1981-2010). In this section, we aim to explain "persistent" determinants of business cycle co-movement. Thus, we use a cross-sectional analysis and incorporate a broader set of determinants into the model. In particular, in addition to the 15 determinants considered in the short-run analysis, we include the factors described in section 3.1.2. As we want to explain persistent business cycle co-movement between two countries, we use the absolute difference transformation of most of the determinants to capture differences in economic, financial, demographic, social, cultural, and political factors between the two countries.

Implementing BMA is computationally intractable in this case since there are 2^{47} candidate models to be estimated. Therefore, we use the Markov Chain Monte Carlo Model Composition (MC^3) algorithm, proposed by Madigan and York (1995), which allows us to implement Bayesian model averaging without evaluating every possible model.[28] In particular, the algorithm takes draws from the parameter space, which are made to mimic draws from the posterior by taking many draws from regions of the parameter space where the posterior probability is high and by taking few draws from regions where the posterior probability is low.[29]

Column (1) of Table 7 shows the results of the MC^3 for 36 countries.[30] The most robust "persistent" determinants of business cycle interdependence are bilateral trade and financial openness; these results are consistent with the findings from the short-run analysis. Fiscal factors, such as differences in government budget and international debt issues are also robust determinants. The most robust determinants among the social and cultural factors are differences in religion fractionalization, population (consistent with the findings of Sala i Martin,

[28]The MC^3 algorithm was not implemented in the short-run analysis, since we only have 2^{15} candidate models.

[29]See Koopman (2003) for further details on the MC^3 algorithm.

[30]Africa, Taiwan, China, Iraq, Iceland and Greece were excluded as they do not have information for all the determinants.

2000), fertility rates, and economic freedom. On the financial side, differences in return on assets are a robust determinant of business cycle interdependence. Finally, factors that are key in determining countries' long run growth also help explain ergodic business cycle synchronization, such as investment share, gross capital formation, and total factor productivity.

In section 2.2, we found evidence of a stable clustering pattern among countries based on their business cycle co-movement. To evaluate whether the main determinants vary across groups of countries, we implement our Bayesian model averaging approach in two different groups of countries. The first group, which includes developed countries, is obtained by merging the "Euro area" and "Anglo-Saxon" clusters. The second group, which includes developing countries, is obtained merging the "Asian Tigers" and "emerging markets" clusters. According to column (2) of Table 7, the main "persistent" determinants for developed countries are bilateral trade, differences in investment share, differences in the human development index, differences in foreign direct investment, differences in government fractionalization, differences in credit to government and state enterprises, and differences in international debt. Financial openness, differences in linguistic fractionalization, urban population, human capital, Gini index, and differences in the largest government party orientation also have a high posterior inclusion probability. For developing countries, the results for which are presented in column (3), we find that the most robust "persistent" determinants are differences in fertility rate, differences in human capital, differences in stock market total value traded, differences in the largest government party orientation, and differences in return on assets. [31]

Business cycle interdependence in developed countries seems to be mainly attributed to commonalities in economic factors, while financial factors are the most relevant determinants of business cycle synchronization in developing countries. Note that since the early 2000s, developing economies have not only experienced higher co-movement but also witnessed a continuously increase in their overall contribution to world GDP, as shown in Figure 10.

4 Robustness

In this section, we check the robustness of the results to the assumptions made in the identification of the main drivers of business cycle interdependence. First, we present results for an

[31] For robustness purposes we also performed an adaptive version of the MC^3 algorithm, proposed by Lamnisos et al. (2013), which identifies redundant variables and assign them lower probabilities of selection, thereby improving the efficiency of the MCMC method. However, the results were qualitatively the same. They are not reported for the sake of brevity.

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 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 (Table 8) and in the dynamic panel (Table 9) models. The only exception is that the posterior inclusion probability of bilateral trade is now significantly lower. We also find that after the break, the most important determinant is similarity in sectoral composition (Table 10).

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 Tables 11 and 12 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. Moreover, the economic impact of all the robust determinants does not substantially vary between BMA and WALS. Therefore, our results are robust to the use of different g-priors and model averaging techniques.

5 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 Markov-switching 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 these methodologies to measure the probability that a shock in a particular economy will be transmitted to their economy. The second part of the paper focuses on identifying the most important factors explaining variation in business cycle co-movement in the short and long run. 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 in the short and long run are bilateral trade and financial openness. Other important factors that explain changes in business cycle co-movement are consumption share, inflation, and human capital. However, the importance of these determinants, measured by their inclusion probability, varies across time. In particular, we find that the most robust determinant after the increase in global business cycle interdependence is similarity in countries' industrial composition.

The determinants of business cycle co-movement also vary across countries of different levels of economic development. On the one hand, economic factors such as bilateral trade, investment share, and foreign direct investment share are crucial factors explaining variation in business cycle co-movement across developed countries. On the other hand, financial factors such as return on assets, financial openness, and stock market total value traded are important factors explaining changes in business cycle synchronization across developing countries.

These results also have important implications for policy makers. If policy makers aim to reduce the probability that shocks to other countries are propagated to their economy, they should closely monitor their amount of financial assets and liquid liabilities with other economies and their dependency on trade with other economies, given their sectoral composition.

Our study has some limitations. We cannot claim any causal effect between the determinants and business cycle co-movement, as our Bayesian model averaging approach does not address reverse causality. Future research could focus on the simultaneous estimation of the most important determinants found in this paper: financial openness, bilateral trade, human capital, inflation, and consumption share. However, finding time-varying exogenous variation for all

these determinants would be challenging.

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

$$s_{ab,t} = \begin{cases} 1 \text{ if } s_{a,t} = 0 \text{ and } s_{b,t} = 0 \\ 2 \text{ if } s_{a,t} = 1 \text{ and } s_{b,t} = 0 \\ 3 \text{ if } s_{a,t} = 0 \text{ and } s_{b,t} = 1 \\ 4 \text{ if } s_{a,t} = 1 \text{ and } s_{b,t} = 1 \end{cases}, \tag{25}$$

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.[32]

$$s^*_{ab,t} = \begin{cases} 1 \text{ if } s_{a,t} = 0,\ s_{b,t} = 0, \text{ and } v_{ab,t} = 0 \\ 2 \text{ if } s_{a,t} = 1,\ s_{b,t} = 0, \text{ and } v_{ab,t} = 0 \\ 3 \text{ if } s_{a,t} = 0,\ s_{b,t} = 1, \text{ and } v_{ab,t} = 0 \\ 4 \text{ if } s_{a,t} = 1,\ s_{b,t} = 1, \text{ and } v_{ab,t} = 0 \\ 5 \text{ if } s_{a,t} = 0,\ s_{b,t} = 0, \text{ and } v_{ab,t} = 1 \\ 6 \text{ if } s_{a,t} = 1,\ s_{b,t} = 0, \text{ and } v_{ab,t} = 1 \\ 7 \text{ if } s_{a,t} = 0,\ s_{b,t} = 1, \text{ and } v_{ab,t} = 1 \\ 8 \text{ if } s_{a,t} = 1,\ s_{b,t} = 1, \text{ and } v_{ab,t} = 1 \end{cases}. \tag{26}$$

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

$$p\left(s^*_{ab,t} = i^*_{ab} | \widetilde{y}_{ab,t-1}, \theta\right) \tag{27}$$

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

$$f_{ab}\left(y_{ab,t} | \widetilde{y}_{ab,t-1}, \theta\right) = \sum_{i=1}^{8} f_{ab}\left(y_t | s^*_{ab,t} = j^*_{ab}, \widetilde{y}_{ab,t-1}, \theta\right) p\left(s^*_{ab,t} = j^*_{ab} | \widetilde{y}_{ab,t-1}, \theta\right), \tag{28}$$

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

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

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

$$p\left(s^*_{ab,t}=j^*_{ab}|\widetilde{y}_{ab,t-1},\theta\right)=p\left(s_{ab,t}=j_{ab}|v_{ab,t}=j_v,\widetilde{y}_{ab,t-1},\theta\right)p\left(v_{ab,t}=j_v|\widetilde{y}_{ab,t-1},\theta\right), \tag{29}$$

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

$$p\left(s_{ab,t}=j_{ab}|v_{ab,t}=0,\widetilde{y}_{ab,t-1},\theta\right)=p\left(s_{a,t}=j_a|\widetilde{y}_{ab,t-1},\theta\right)p\left(s_{b,t}=j_b|\widetilde{y}_{ab,t-1},\theta\right), \tag{30}$$

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 (25), where states 2 and 3 never occur and where the two countries share the cycle in states 1 and 4. In this case, the probability term is

$$p\left(s_{ab,t}=j_{ab}|v_{ab,t}=1,\widetilde{y}_{ab,t-1},\theta\right)=p\left(\varsigma_{ab,t}=j_{ab}|\widetilde{y}_{ab,t-1},\theta\right), \tag{31}$$

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

$$p\left(\varsigma_{ab,t}=j_{ab}|\varsigma_{ab,t-1}=i_{ab},\varsigma_{ab,t-2}=h_{ab},...,\widetilde{y}_{ab,t-1}\right)=p\left(\varsigma_{ab,t}=j_{ab}|\varsigma_{ab,t-1}=i_{ab}\right)=q^{ab}_{ij}. \tag{32}$$

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:

$$p\left(s_{k,t}=j_k|\widetilde{y}_{ab,t},\theta\right) = f_k\left(y_{k,t}|s_{k,t}=j_k,\widetilde{y}_{ab,t-1},\theta\right)p\left(s_{k,t}=j_k|\widetilde{y}_{ab,t-1},\theta\right)/f_k\left(y_{k,t}|\widetilde{y}_{ab,t-1},\theta\right), \tag{33}$$

$$p\left(v_{ab,t}=j_v|\widetilde{y}_{ab,t},\theta\right) = f_{ab}\left(y_{ab,t}|v_{ab,t}=j_v,\widetilde{y}_{ab,t-1},\theta\right)p\left(v_{ab,t}=j_v|\widetilde{y}_{ab,t-1},\theta\right)/f_{ab}\left(y_{ab,t}|\widetilde{y}_{ab,t-1},\theta\right), \tag{34}$$

$$p\left(\varsigma_{ab,t}=j_{ab}|\widetilde{y}_{ab,t},\theta\right) = f_{ab}\left(y_{ab,t}|\varsigma_{ab,t}=j_{ab},\widetilde{y}_{ab,t-1},\theta\right)p\left(\varsigma_{ab,t}=j_{ab}|\widetilde{y}_{ab,t-1},\theta\right)/f_{ab}\left(y_{ab,t}|\widetilde{y}_{ab,t-1},\theta\right), \tag{35}$$

where $f_k\left(\bullet\right)$ 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:

$$p\left(s_{k,t+1}=j_k|\widetilde{y}_{ab,t},\theta\right) = \sum_{i_k=0}^{1} p\left(s_{k,t}=i_k|\widetilde{y}_{ab,t},\theta\right) p_{ij}^{k}, \tag{36}$$

$$p\left(v_{ab,t+1}=j_v|\widetilde{y}_{ab,t},\theta\right) = \sum_{i=0}^{1} p\left(v_{ab,t}=i_v|\widetilde{y}_{ab,t},\theta\right) p_{ij}^{ab}, \tag{37}$$

$$p\left(\varsigma_{ab,t+1}=j_{ab}|\widetilde{y}_{ab,t},\theta\right) = \sum_{i=1}^{4} p\left(\varsigma_{ab,t}=i_{ab}|\widetilde{y}_{ab,t},\theta\right) q_{ij}^{ab}. \tag{38}$$

Then, the joint probabilities $p\left(s_{ab,t+1}^{*}=j_{ab}^{*}|\widetilde{y}_{ab,t},\theta\right)$ can be updated by using (29), 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 $N\left(N-1\right)/2$ 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,

$$\min_{\tilde{\gamma}_t^{ij}} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}(\gamma_t^{ij} - \tilde{\gamma}_t^{ij})^2}{\sum_{i,i}(\gamma_t^{ij})^2} + \beta \sum_{i=1}^{n} \tilde{\gamma}_{t|t-1}^{i}, \tag{39}$$

where

$$\tilde{\gamma}_t^{ij} = (||z_{i,t} - z_{j,t}||^2)^{1/2} \tag{40}$$

$$\tilde{\gamma}_{t|t-1}^{i} = (||z_{i,t} - z_{i,t-1}||^2)^{1/2}, \tag{41}$$

$z_{i,t}$ 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 (39) provides a two-dimensional representation of the matrix of business cycle distances.

Appendix D: Variable Definitions

S 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.

- *Bank Returns on Assets (%, after tax)* Commercial banks' after-tax net income to yearly averaged total assets. Source: Global Financial Development Report, The World Bank, 2013.

- *Civil Liberties* include freedom of speech, expression and the press; freedom of religion; freedom of assembly and association; and the right to due judicial process. Source: The Quality of Government Institute, 2013.

- Share of household *Consumption* at current PPPs is the sum of household final consumption expenditure (private consumption) and general government final consumption expenditure (general government consumption). Source: Penn World Table 8.0.

- *Competition* measures the electoral success of smaller parties, that is, the percentage of votes gained by the smaller parties in parliamentary and/or presidential elections. Source: The Quality of Government Institute, 2013.

- *Corruption Perception Index* The CPI focuses on corruption in the public sector and defines corruption as the abuse of public office for private gain. The CPI Score relates to perceptions of the degree of corruption as seen by business people, risk analysts and the general public and ranges between 10 (highly clean) and 0 (highly corrupt). Source: The Quality of Government Institute, 2013.

- *Credit to government and state owned enterprises to GDP (%)* is the ratio between credit by domestic money banks to the government and state-owned enterprises and GDP. 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.

- *Economic Freedom of the World Index* The index is founded upon objective components that reflect the presence (or absence) of economic freedom. The index comprises 21 components designed to identify the consistency of institutional arrangements and policies with economic freedom in five major areas: size of government, legal structure and security of property rights, access to sound money, freedom to trade internationally, regulation of credit, labor and business. This is the version of the index obtained using the chain-linked methodology. Source: The Quality of Government Institute, 2013.

- *Economic globalization* is defined as the long distance flows of goods, capital and services as well as information and perceptions that accompany market exchanges. It is measured by actual flows of trade and investments, and by restrictions on trade and capital such as tariff rates. Source: The Quality of Government Institute, 2013.

- *Environmental Performance Index* is a composite index that measures how well countries succeed in reducing environmental stresses on human health and promoting ecosystem vitality and sound natural resource management. Source: The Quality of Government Institute, 2013.

- *Ethnic Fractionalization* reflects probability that two randomly selected people from a given country will not belong to the same ethnolinguistic group. Source: The Quality of Government Institute, 2013.

- *Exchange Rate* refers to the exchange rate determined by national authorities or to the rate determined in the legally sanctioned exchange market. It is calculated as an annual average based on monthly averages (local currency units relative to the U.S. dollar). Source: World Development Indicator, 2013.

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

- *Fertility* represents the number of children that would be born to a woman if she were to live to the end of her childbearing years and bear children in accordance with current age-specific fertility rates. Source: World Development Indicator, 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.

- *Foreign Direct Investment* are the net inflows of investment to acquire a lasting management interest in an enterprise operating in an economy other than that of the investor. It is the sum of equity capital, reinvestment of earnings, other long-term capital, and short-term capital as shown in the balance of payments. This series shows net outflows of investment from the reporting economy to the rest of the world and is divided by GDP. Source: World Development Indicator, 2013.

- *Gender Inequality* A composite measure reflecting inequality in achievements between women and men in three dimensions: reproductive health, empowerment and the labour market. See Technical note 3 at $http://hdr.undp.org/en/media/HDR_2012_ENTechNotes.pdf$

for details on how the Gender Inequality Index is calculated. Source: United Nations Development Programme, 2013.

- *Gini Index* measures the extent to which the distribution of income or consumption expenditure among individuals or households within an economy deviates from a perfectly equal distribution. Source: World Development Indicator, 2013.

- The *Globalization* index is the weighted average of the following variables: economic globalization, social globalization and political globalization. Most weight has been given to economic followed by social globalization. Source: The Quality of Government Institute, 2013.

- *Government Budget Deficit/Surplus (% of GDP)* The government budget deficit or surplus as a percentage of GDP. Source: IMF, Government Finance Statistics, 2013.

- *Government Fractionalization* measures the probability that two randomly chosen deputies from among the government parties will be of different parties. Source: The Quality of Government Institute, 2013.

- Share of *Government* consumption at current PPPs. Government consumption consists of spending on government administration, education and health, activities which are typically among the least exposed to international trade. Source: Penn World Table 8.0.

- Share of *Gross Capital Formation* at current PPPs. Source: Penn World Table 8.0.

- *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.

- The *Human Development Index* is a composite index that measures the average achievements in a country in three basic dimensions of human development: a long and healthy life, as measured by life expectancy at birth; knowledge, as measured by the adult literacy rate and the combined gross enrolment ratio for primary, secondary and tertiary schools; and a decent standard of living, as measured by GDP per capita in purchasing

power parity (PPP) US dollars. See http://hdr.undp.org/en/statistics/hdi for details on how the Human Development Index is calculated. Source: United Nations Development Programme, 2013.

- *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.

- *Infant mortality* Number of infants dying before reaching one year of age. Source: World Development Indicator, 2013.

- *Inflation* as measured by the consumer price index reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals, such as yearly. The Laspeyres formula is generally used. Source: World Development Indicator, 2013.

- *Internet Users* (per 100 People). Source: World Development Indicator, 2013. Source: International Telecommunication Union, 2013.

- *International Debt Issues (% of GDP)* Total value of outstanding international debt issues both public and private, as a share of GDP. Source: Global Financial Development Report, The World Bank, 2013.

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

- *Largest Government Party Orientation* codes whether the largest government party is right, left or center oriented. Source: The Quality of Government Institute, 2013.

- *Linguistic Fractionalization* reflects probability that two randomly selected people from a given country will not belong to the same linguistic group. Source: The Quality of Government Institute, 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.

- *Political Globalization* is measured by the number of embassies and high commissions in a country, the number of international organizations of which the country is a member, the number of UN peace missions the country has participated in, and the number of international treaties that the country has signed since 1945. Source: The Quality of Government Institute, 2013.

- *Political Constraint Index* measures the feasibility of policy change, i.e. the extent to which a change in the preferences of any one political actor may lead to a change in government policy. See the Quality of Government Institute codebook at $http://www.qogdata.pol.gu.se/codebook/codebook_standard_20dec13.pdf$ for more details. Source: The Quality of Government Institute, 2013.

- *Political Stability* combines several indicators which measure perceptions of the likelihood that the government in power will be destabilized or overthrown by possibly unconstitutional and/or violent means, including domestic violence and terrorism. Source: The Quality of Government Institute, 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.

- *Religious Fractionalization* reflects probability that two randomly selected people from a given country will not belong to the same religious group. Source: The Quality of Government Institute, 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.

- *Social Globalization* is measured by three categories of indicators. The first is personal contacts, such as telephone traffic and tourism. The second is information flows, e.g. number of Internet users. The third is cultural proximity, e.g. trade in books and number of Ikea warehouses per capita. Source: The Quality of Government Institute, 2013.

- *Stock Market Total Value Traded to GDP* refers to the total value of shares traded during the period. Source: Global Financial Development Report, The World Bank, 2013.

- *Tax Revenue* refers to compulsory transfers to the central government for public purposes. Source: World Development Indicator, 2013.

- *Total Factor Productivity* measures the overall productivity of one country relative to another, holding fixed the level of factor endowments. See the Next Generation of the Penn World Table at $http://www.rug.nl/research/ggdc/data/pwt/v80/$ for details on how the total factor productivity is computed. Source: Penn World Table 8.0.

- *Unemployment* is the share of the labor force that is without work but available for and seeking employment. 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.

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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)
Consumption Share diff.	0.6651(0.0000)
Inflation diff. (%)	0.0417(0.0000)
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)
Foreign Direct Investment (% of GDP)diff.	0.1540(0.0000)
Investment Share diff.	0.6736(0.0000)
Financial System Deposit to GDP diff.	0.7715(0.7846)
Gross capital formation diff.	0.6282(0.0000)
Private Credit to GDP diff.	0.8458(1.0000)
Exchange Rate diff.	0.9726(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: A BMA approach. Hyper-g-prior. Static panel. Period: 1981-2010

	PI prob.	Pt. Mean	Pt. Std.	Sign	t-stat.
Consumption Share diff.	0.9999	0.0243	0.0051	1.0000	4.7184
Inflation (%) diff.	0.9995	0.0185	0.0045	1.0000	4.1559
Financial Openness	0.9980	0.0320	0.0085	1.0000	3.7651
Human Capital index diff.	0.9954	0.2109	0.0602	1.0000	3.5046
Bilateral Trade	0.9582	-1.3627	0.5559	0.0000	-2.4512
Liquid Liabilities to GDP diff.	0.7879	-0.0072	0.0053	0.0000	-1.3644
Foreign Direct Investment (% of GDP) diff.	0.6253	-0.0001	0.0001	0.0000	-0.9254
Private Credit to GDP diff.	0.5222	0.0023	0.0032	1.0000	0.7009
Investment Share diff.	0.4338	-0.0020	0.0041	0.0001	-0.4936
Financial System Deposit to GDP diff.	0.3850	0.0005	0.0017	0.8826	0.2821
Exchange Rate diff.	0.3805	-0.0002	0.0007	0.0000	-0.2969
Difference of sectoral composition	0.3752	0.0023	0.0088	1.0000	0.2677
Gross capital formation diff.	0.3677	0.0019	0.0092	1.0000	0.2099
Government Expenditure(% of GDP) diff.	0.3588	0.0003	0.0029	0.8975	0.1081
Urban population diff. (% of total population)	0.3574	-0.0030	0.0304	0.0000	-0.0983

Column 1 presents the posterior inclusion probability. Column 2 shows the weighted average posterior mean. Column 3 reports the weighted average posterior standard deviation. Column 4 shows changes in the sign of the determinant across specifications; it is equal to 1 if the sign of the determinant is positive in all specifications and 0 if it is negative in all specifications, and values between 0 and 1 indicate that the sign of the determinant changes across the candidate models. Column 5 presents the ratio of the weighted posterior mean to the weighted posterior standard deviation. 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.

Table 4: Determinants of business cycle de-synchronization: A BMA approach. Hyper g-prior. Dynamic panel. Period: 1981-2010

	PI prob.	Pt. Mean	Pt. Std.	Sign	t-stat.
De-synchronization$_{t-1}$	1.0000	0.1829	0.0094	1.0000	19.4809
De-synchronization$_{t-2}$	1.0000	-0.1724	0.0093	0.0000	-18.4756
Consumption Share diff.	1.0000	0.0267	0.0049	1.0000	5.4750
Inflation (%) diff.	0.9998	0.0207	0.0044	1.0000	4.6741
Financial Openness	0.9886	0.0309	0.0090	1.0000	3.4509
Human Capital index diff.	0.9467	0.1841	0.0723	1.0000	2.5467
Bilateral Trade	0.6652	-0.8016	0.6935	0.0000	-1.1559
Liquid Liabilities to GDP diff.	0.5924	-0.0056	0.0056	0.0000	-0.9994
Foreign Direct Investment (% of GDP) diff.	0.2820	-0.0001	0.0001	0.0000	-0.5035
Gross capital formation diff.	0.2283	-0.0016	0.0039	0.0000	-0.4190
Private Credit to GDP diff.	0.1362	0.0003	0.0015	0.9932	0.2091
Investment share diff.	0.1349	0.0014	0.0065	1.0000	0.2180
Financial System Deposit to GDP diff.	0.1220	-0.0001	0.0009	0.5522	-0.0591
Exchange Rate diff.	0.1128	0.0000	0.0004	0.0020	-0.0875
Urban population diff. (% of total population)	0.1125	-0.0015	0.0179	0.0000	-0.0855
Government Expenditure(% of GDP) diff.	0.1119	0.0001	0.0017	0.7043	0.0447
Difference of sectoral composition	0.1106	0.0003	0.0046	0.9982	0.0565

Column 1 presents the posterior inclusion probability. Column 2 shows the weighted average posterior mean. Column 3 reports the weighted average posterior standard deviation. Column 4 shows changes in the sign of the determinant across specifications; it is equal to 1 if the sign of the determinant is positive in all specifications and 0 if it is negative in all specifications, and values between 0 and 1 indicate that the sign of the determinant changes across the candidate models. Column 5 presents the ratio of the weighted posterior mean to the weighted posterior standard deviation. 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.

Table 5: Determinants of business cycle de-synchronization before and after the break: A BMA approach. Hyper-g-prior. Static panel

BEFORE THE BREAK (period: 1981-)	1999	2000	2001	2002
Consumption Share diff.	**0.9985**	**0.9993**	**1.0000**	**1.0000**
Inflation (%) diff.	**0.9997**	**1.0000**	**0.9999**	**0.9999**
Financial Openness	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Human Capital index diff.	**0.9993**	**0.9948**	**0.9963**	**0.9929**
Bilateral Trade	**0.9629**	**0.9969**	**0.9884**	**0.9672**
Liquid Liabilities to GDP diff.	**0.9785**	**0.9192**	**0.8887**	**0.9143**
Foreign Direct Investment (% of GDP) diff.	**0.9681**	0.4963	**0.8293**	0.4861
Investment Share diff.	0.6161	0.6052	0.5127	0.4726
Financial System Deposit to GDP diff.	0.5984	0.4443	0.5029	0.4258
Gross capital formation diff.	**0.9233**	0.6079	0.6390	0.5085
Private Credit to GDP diff.	0.6627	0.6320	**0.8385**	**0.8366**
Exchange Rate diff.	0.5652	0.4354	0.4787	0.4113
Urban population diff. (% of total population)	0.6433	0.4966	0.5163	0.4349
Difference of sectoral composition	**0.9472**	**0.9530**	**0.9337**	**0.8729**
Government Expenditure(% of GDP) diff.	0.5624	0.4283	0.4850	0.4122
AFTER THE BREAK (period: -2010)	2000	2001	2002	2003
Consumption Share diff.	0.6157	0.3390	0.4794	0.4060
Inflation (%) diff.	0.5753	0.3659	0.4792	0.3746
Financial Openness	0.6467	0.4044	0.6011	0.5111
Human Capital index diff.	**0.8521**	0.6151	**0.8952**	**0.8018**
Bilateral Trade	0.5361	0.3189	0.5034	0.4007
Liquid Liabilities to GDP diff.	**0.8877**	0.4646	**0.8369**	0.5755
Foreign Direct Investment (% of GDP) diff.	0.6079	0.3280	0.5099	0.5112
Investment Share diff.	**0.9596**	0.6443	**0.9501**	**0.8469**
Financial System Deposit to GDP diff.	0.5387	0.3362	0.4870	0.5872
Gross capital formation diff.	0.5612	0.3383	0.4956	0.3870
Private Credit to GDP diff.	0.6166	0.3175	0.4818	0.3791
Exchange Rate diff.	**0.8847**	0.3765	0.7332	**0.8024**
Urban population diff. (% of total population)	0.6475	0.4126	0.5299	0.4159
Difference of sectoral composition	**0.9863**	**0.8089**	**0.9831**	**0.9994**
Government Expenditure(% of GDP) diff.	**0.8152**	0.4784	0.6204	0.5302

The sample period considered before the break is from 1980 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 6: Determinants of ergodic business cycle de-synchronization: A BMA approach. Hyper g-prior. Average across period 1981-2010

	PI prob.	Pt. Mean	Pt. Std.	Sign	t-stat.
Urban population diff. (% of total population)	1.0000	0.4019	0.0876	1.0000	4.5856
Financial Openness	0.9997	-0.2109	0.0469	0.0000	-4.5012
Gross capital formation diff.	0.9339	0.5364	0.2535	1.0000	2.1156
Bilateral Trade	0.9127	-3.1911	1.6633	0.0000	-1.9186
Liquid Liabilities to GDP diff.	0.9104	0.2151	0.1315	1.0000	1.6357
Investment share diff.	0.7678	0.1332	0.1053	1.0000	1.2649
Difference of sectoral composition	0.7180	0.0654	0.0611	1.0000	1.0703
Financial System Deposit to GDP diff.	0.6911	-0.1169	0.1164	0.0446	-1.0047
Exchange Rate diff.	0.5678	0.0044	0.0056	1.0000	0.7904
Private Credit to GDP diff.	0.5411	0.0263	0.0370	1.0000	0.7112
Inflation (%) diff.	0.4817	-0.9660	1.5976	0.0001	-0.6046
Consumption Share diff.	0.4313	-0.0218	0.0654	0.1639	-0.3333
Human Capital index diff.	0.4089	-0.8966	2.5469	0.0347	-0.3520
Government Expenditure(% of GDP) diff.	0.4018	0.0094	0.0390	0.9004	0.2424
Foreign Direct Investment (% of GDP) diff.	0.3894	-0.0019	0.0103	0.2337	-0.1876

Column 1 presents the posterior inclusion probability. Column 2 shows the weighted average posterior mean. Column 3 reports the weighted average posterior standard deviation. Column 4 shows changes in the sign of the determinant across specifications; it is equal to 1 if the sign of the determinant is positive in all specifications and 0 if it is negative in all specifications, and values between 0 and 1 indicate that the sign of the determinant changes across the candidate models. Column 5 presents the ratio of the weighted posterior mean to the weighted posterior standard deviation. 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.

Table 7: Determinants of ergodic business cycle de-synchronization: A BMA approach. Hyper-g-prior. Average across period 1981-2010

	All countries	Developed countries	Developing countries
	PI prob.	PI prob.	PI prob.
Bilateral Trade	**1.0000**	**0.9940**	0.5427
Fertility rate diff.	**1.0000**	0.5381	**0.9525**
Financial Openness	**1.0000**	**0.8035**	0.6529
Government Budget Deficit/Surplus	**0.9941**	0.6758	0.5538
Return on Assets diff.	**0.9928**	0.4810	**0.8088**
Total Factor Productivity	**0.979**	0.4771	0.7228
International Debt Issues to GDP	**0.9656**	**0.9022**	0.5821
Population diff.	**0.8937**	0.4551	0.5572
Investment Share diff.	**0.8756**	**0.9889**	0.6578
Economic Freedom World index diff.	**0.8677**	0.6569	0.6221
Gross capital formation diff.	**0.8554**	0.4329	0.5848
Religion Fractionalization diff.	**0.8343**	0.6040	0.5481
Corruption Perception Index diff.	0.7684	0.7511	0.6363
Economic Globalization diff.	0.7333	0.4886	0.5518
Political Constraints index diff.	0.7216	0.4791	0.5684
Private Credit Growth diff.	0.6744	0.5324	0.5466
Deposit diff.	0.6657	0.4714	0.5620
Infant Mortality rate diff.	0.6047	0.4805	0.5760
Urban population diff. (% of total population)	0.6028	**0.8560**	0.5495
Political Stability index diff.	0.5684	0.7281	0.5430
Foreign Direct Investment (% of GDP) diff.	0.5568	**0.9647**	0.5849
Civil Liberties diff.	0.5264	0.5093	0.5671
Unemployment (%) diff.	0.5049	0.4371	0.6818
Exchange Rate diff.	0.4598	0.4634	0.5837
Government Fractionalization index diff.	0.4589	**0.9301**	0.5165
Bank Credit to GDP diff.	0.4426	0.4356	0.6096
Gender Inequality index diff.	0.4355	0.5669	0.7281
Political Globalization	0.4140	0.4293	0.5849
Difference of sectoral composition	0.4088	0.5658	0.5215
Linguistic Fractionalization diff.	0.3679	**0.8588**	0.7121
Environmental Performance index diff.	0.3621	0.5070	0.5279
Human Development index diff.	0.3494	**0.9886**	0.5648
Human Capital diff.	0.3449	**0.8093**	**0.8649**
Social Globalization diff.	0.3399	0.6975	0.5606
Credit to Government diff.	0.3354	**0.9295**	0.7220
Consumption Share diff.	0.3270	0.7512	0.7362
Tax Revenue diff.	0.3268	0.3995	0.5611
Competition index diff.	0.3247	0.6993	0.5477
Largest Government Party Orientation diff.	0.3202	**0.8000**	**0.8331**
Internet Users (per 100 people) diff.	0.3157	0.4798	0.6214
Liquid liabilities to GDP diff.	0.2990	0.4908	0.5441
Inflation (%) diff.	0.2982	0.4363	0.5446
Private Credit to GDP	0.2956	0.4058	0.6590
Gini index diff.	0.2949	**0.8324**	0.5194
Stock market total value traded to GDP diff.	0.2828	0.4751	**0.8559**
Ethnic fractionalization diff.	0.2783	0.4753	0.6235
Government Expenditure(% of GDP) diff.	0.2732	0.7213	0.6812

Results obtained from using the MC^3 algorithm for BMA. The dependent variable is ergodic 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 the hyper-g-prior. Entries higher than 0.8 are presented in bold.

Table 8: Determinants of business cycle de-synchronization: A BMA approach. BRIC g-prior. Static panel. Period: 1981-2010

	PI prob.	Pt. Mean	Pt. Std.	Sign	t-stat.
Consumption Share diff.	0.9999	0.0255	0.0042	1.0000	6.0547
Inflation (%) diff.	0.9741	0.0193	0.0055	1.0000	3.5029
Financial Openness	0.9308	0.0330	0.0123	1.0000	2.6786
Human Capital index diff.	0.8151	0.1879	0.1051	1.0000	1.7885
Bilateral Trade	0.3067	-0.4774	0.7709	0.0000	-0.6192
Liquid Liabilities to GDP diff.	0.0395	-0.0003	0.0018	0.0000	-0.1825
Foreign Direct Investment (% of GDP) diff.	0.0174	0.0000	0.0000	0.0000	-0.1136
Investment Share diff.	0.0074	0.0000	0.0006	0.0002	-0.0610
Private Credit to GDP diff.	0.0065	0.0000	0.0004	1.0000	0.0520
Exchange Rate diff.	0.0052	0.0000	0.0001	0.0000	-0.0339
Difference of sectoral composition	0.0050	0.0000	0.0011	1.0000	0.0308
Gross capital formation diff.	0.0049	0.0000	0.0012	1.0000	0.0285
Financial System Deposit to GDP diff.	0.0047	0.0000	0.0002	0.0599	-0.0161
Urban population diff. (% of total population)	0.0046	0.0000	0.0036	0.0000	-0.0127
Government Expenditure(% of GDP) diff.	0.0045	0.0000	0.0003	0.0406	-0.0030

Column 1 presents the posterior inclusion probability. Column 2 shows the weighted average posterior mean. Column 3 reports the weighted average posterior standard deviation. Column 4 shows changes in the sign of the determinant across specification; it is equal to 1 if the sign of the determinant is positive in all specifications and 0 if it is negative in all specifications, and values between 0 and 1 indicate that the sign of the determinant changes across the candidate models. Column 5 presents the ratio of the weighted posterior mean to the weighted posterior standard deviation. 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. The results are obtained by using a hierarchical prior and BRIC prior.

Table 9: Determinants of business cycle de-synchronization: A BMA approach. BRIC g-prior. Dynamic panel. Period: 1981-2010

	PI prob.	Pt. Mean	Pt. Std.	Sign	t-stat.
De-synchronization$_{t-1}$	1.0000	0.1854	0.0094	1.0000	19.6611
De-synchronization$_{t-2}$	1.0000	-0.1741	0.0094	0.0000	-18.5564
Consumption Share diff.	1.0000	0.0262	0.0041	1.0000	6.3570
Inflation (%) diff.	0.9969	0.0209	0.0046	1.0000	4.5693
Financial Openness	0.8806	0.0284	0.0131	1.0000	2.1685
Human Capital index diff.	0.5610	0.1113	0.1081	1.0000	1.0297
Bilateral Trade	0.1177	-0.1452	0.4317	0.0000	-0.3365
Liquid Liabilities to GDP diff.	0.0843	-0.0008	0.0029	0.0000	-0.2775
Foreign Direct Investment (% of GDP) diff.	0.0193	0.0000	0.0000	0.0000	-0.1179
Investment Share diff.	0.0163	-0.0001	0.0012	0.0000	-0.1057
Financial System Deposit to GDP diff.	0.0081	0.0000	0.0003	0.0700	-0.0554
Gross capital formation diff.	0.0077	0.0001	0.0016	1.0000	0.0535
Private Credit to GDP diff.	0.0060	0.0000	0.0003	0.7143	0.0150
Exchange Rate diff.	0.0059	0.0000	0.0001	0.0009	-0.0187
Urban population diff. (% of total population)	0.0059	-0.0001	0.0042	0.0000	-0.0191
Difference of sectoral composition	0.0058	0.0000	0.0010	0.9216	0.0106
Government Expenditure(% of GDP) diff.	0.0058	0.0000	0.0004	0.0450	-0.0064

Column 1 presents the posterior inclusion probability. Column 2 shows the weighted average posterior mean. Column 3 reports the weighted average posterior standard deviation. Column 4 shows changes in the sign of the determinant across specification; it is equal to 1 if the sign of the determinant is positive in all specifications and 0 if it is negative in all specifications, and values between 0 and 1 indicate that the sign of the determinant changes across the candidate models. Column 5 presents the ratio of the weighted posterior mean to the weighted posterior standard deviation. 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. The results are obtained by using a hierarchical model prior.

Table 10: Determinants of business cycle de-synchronization before and after the break: A BMA approach. BRIC g-prior. Static panel

BEFORE THE BREAK (period: 1980-)	1999	2000	2001	2002
Consumption Share diff.	**0.999**	**1.000**	**1.000**	**1.000**
Inflation (%) diff.	**1.000**	**0.989**	**0.995**	**0.998**
Financial Openness	**1.000**	**1.000**	**1.000**	**1.000**
Human Capital index diff.	0.780	0.747	0.652	0.709
Bilateral Trade	**0.886**	0.589	0.319	0.429
Liquid Liabilities to GDP diff.	0.132	0.046	0.075	0.115
Foreign Direct Investment (% of GDP) diff.	0.010	0.054	0.009	0.007
Investment Share diff.	0.017	0.007	0.007	0.007
Financial System Deposit to GDP diff.	0.009	0.007	0.007	0.008
Gross capital formation diff.	0.019	0.013	0.010	0.011
Private Credit to GDP diff.	0.013	0.029	0.026	0.014
Exchange Rate diff.	0.008	0.006	0.005	0.006
Urban population diff. (% of total population)	0.011	0.008	0.006	0.006
Difference of sectoral composition	0.273	0.149	0.085	0.334
Government Expenditure(% of GDP) diff.	0.008	0.007	0.006	0.006
AFTER THE BREAK (period: -2010)	2000	2001	2002	2003
Consumption Share diff.	0.005	0.007	0.005	0.005
Inflation (%) diff.	0.003	0.003	0.003	0.112
Financial Openness	0.004	0.007	0.009	0.021
Human Capital index diff.	0.032	0.070	0.046	0.021
Bilateral Trade	0.002	0.003	0.003	0.004
Liquid Liabilities to GDP diff.	0.009	0.057	0.031	0.071
Foreign Direct Investment (% of GDP) diff.	0.003	0.005	0.011	0.007
Investment Share diff.	0.038	0.191	0.043	0.022
Financial System Deposit to GDP diff.	0.004	0.010	0.056	0.393
Gross capital formation diff.	0.003	0.003	0.003	0.004
Private Credit to GDP diff.	0.002	0.003	0.003	0.009
Exchange Rate diff.	0.003	0.015	0.043	0.022
Urban population diff. (% of total population)	0.005	0.004	0.004	0.004
Difference of sectoral composition	**0.964**	**0.948**	**1.000**	**1.000**
Government Expenditure(% of GDP) diff.	0.003	0.005	0.003	0.005

The sample period considered before the break is from 1980 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 BRIC-g prior. Entries higher than 0.8 are presented in bold.

Table 11: Determinants of business cycle de-synchronization: A Weighted Average Least Squares approach. Static panel. Period: 1981-2010

	Coef.	Std.	t-stat.
Inflation (%) diff.	0.0176	0.0043	4.0952
Human Capital index diff.	0.2028	0.0544	3.7250
Financial Openness	0.0261	0.0076	3.4545
Consumption Share diff.	0.0189	0.0057	3.3299
Bilateral Trade	-1.1394	0.4383	-2.5996
Liquid Liabilities to GDP diff.	-0.0057	0.0035	-1.6195
Foreign Direct Investment (% of GDP) diff.	-0.0001	0.0001	-1.1338
Private Credit to GDP diff.	0.0035	0.0032	1.0814
Government Expenditure(% of GDP) diff.	0.0038	0.0046	0.8431
Gross capital formation diff.	0.0065	0.0138	0.4719
Investment Share diff.	-0.0011	0.0050	-0.2244
Financial System Deposit to GDP diff.	0.0004	0.0024	0.1838
Urban population diff. (% of total population)	0.0078	0.0450	0.1729
Exchange Rate diff.	-0.0001	0.0010	-0.0552
Difference of sectoral composition	-0.0002	0.0118	-0.0194

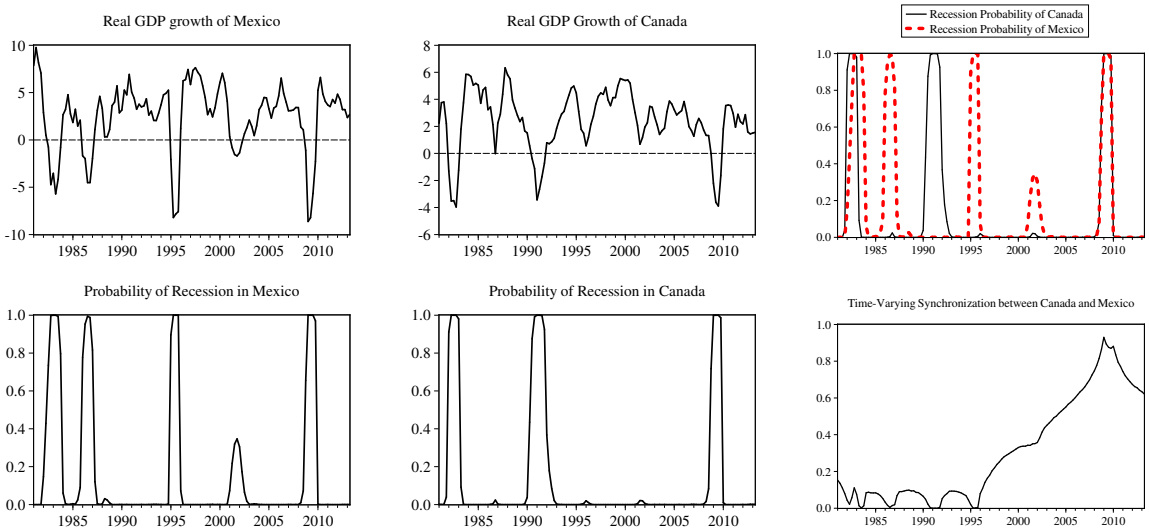
The results are obtained by using the Weighted Average Least Squares approach introduced by Magnus, Powell, and Prufer (2010). Column 1 reports the weighted average coefficients, column 2 presents the weighted average standard deviation, and column 3 shows the t-statistics. Determinants with a t-statistics 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 12: Determinants of business cycle de-synchronization: A Weighted Average Least Squares approach. Dynamic panel. Period: 1981-2010

	Coef.	Std.	t-stat.
De-synchronization$_{t-1}$	0.1757	0.0091	19.2784
De-synchronization$_{t-2}$	-0.1652	0.0092	-17.9388
Inflation (%) diff.	0.0176	0.0040	4.4410
Consumption Share diff.	0.0230	0.0060	3.8554
Financial Openness	0.0264	0.0082	3.2123
Human Capital index diff.	0.1784	0.0584	3.0580
Liquid Liabilities to GDP diff.	-0.0075	0.0042	-1.7844
Bilateral Trade	-0.8034	0.4817	-1.6679
Foreign Direct Investment (% of GDP) diff.	-0.0002	0.0001	-1.5018
Gross capital formation diff.	0.0181	0.0139	1.3010
Investment Share diff.	-0.0039	0.0053	-0.7350
Private Credit to GDP diff.	0.0020	0.0029	0.6928
Government Expenditure(% of GDP) diff.	0.0027	0.0049	0.5539
Urban population diff. (% of total population)	-0.0249	0.0479	-0.5203
Difference of sectoral composition	-0.0045	0.0134	-0.3398
Exchange Rate diff.	-0.0002	0.0010	-0.2185
Financial System Deposit to GDP diff.	0.0003	0.0024	0.1254

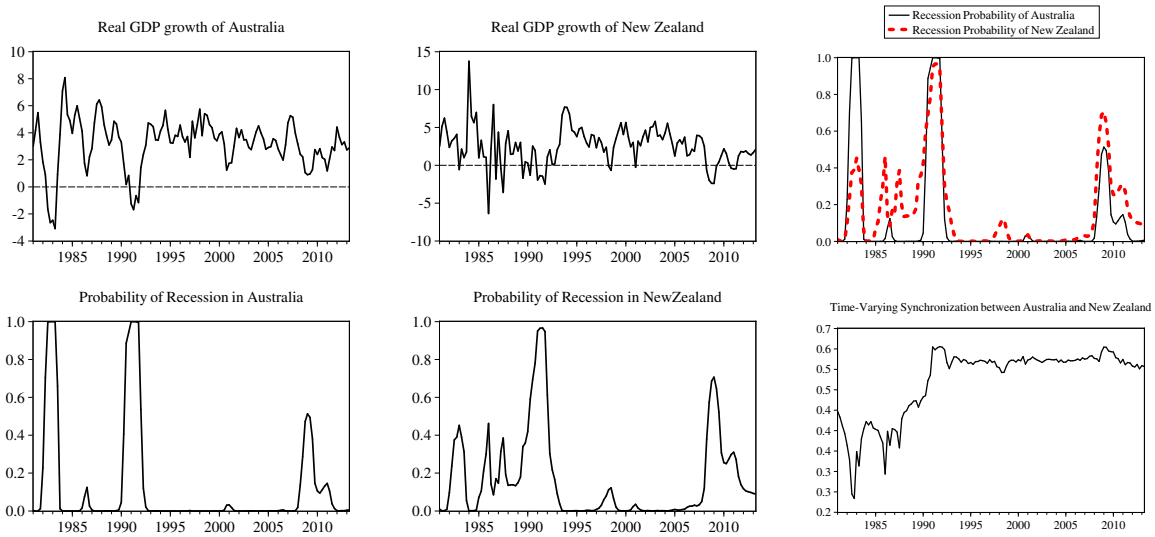
The results are obtained by using the Weighted Average Least Squares introduced by Magnus, Powell, and Prufer (2010). Column 1 reports the weighted average coefficients, column 2 presents the weighted average standard deviation, and column 3 shows the t-statistics. Determinants with a t-statistics larger 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.

Figure 1: Business cycle interdependence between Canada and Mexico



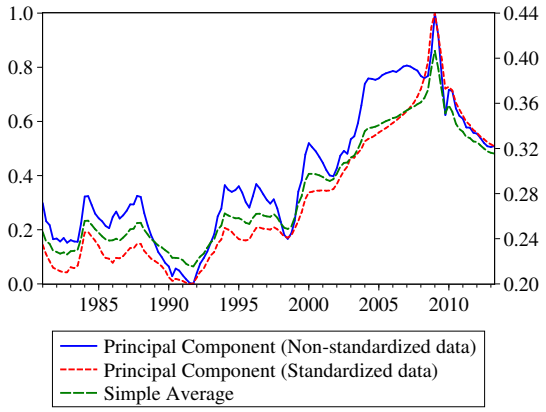
Note: The results shown in the figure come from the bivariate Markov-switching model for the real GDP growth of Mexico and Canada. The sample period is 1981:Q1-2013:Q2.

Figure 2: Business cycle interdependence between Australia and New Zealand



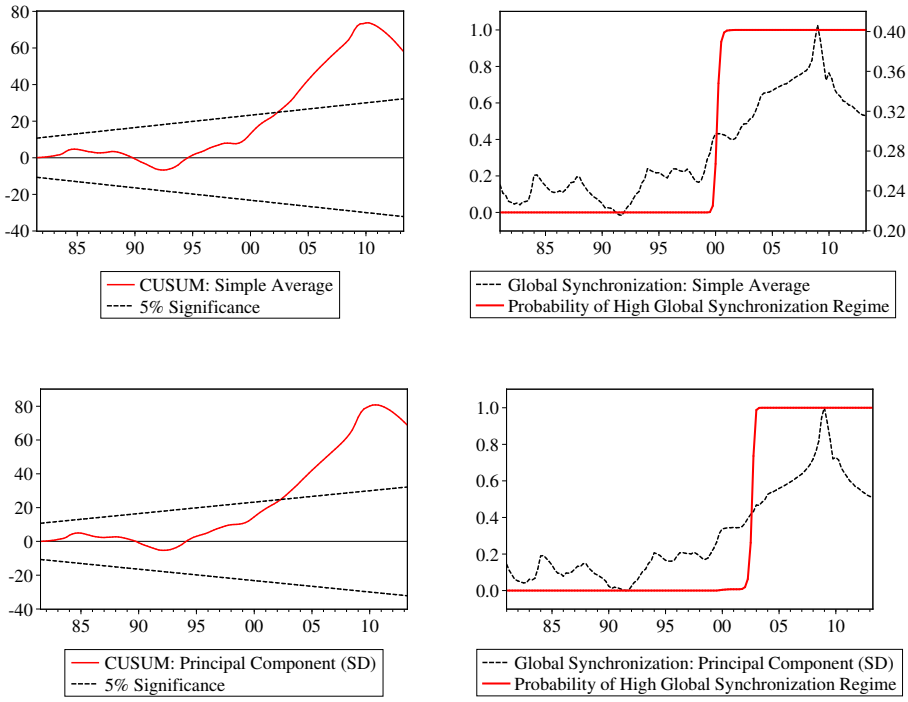
Note: The results shown in the figure come from the bivariate Markov-switching model for the real GDP growth of Australia and New Zealand. The sample period is 1981:Q1-2013:Q2.

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.

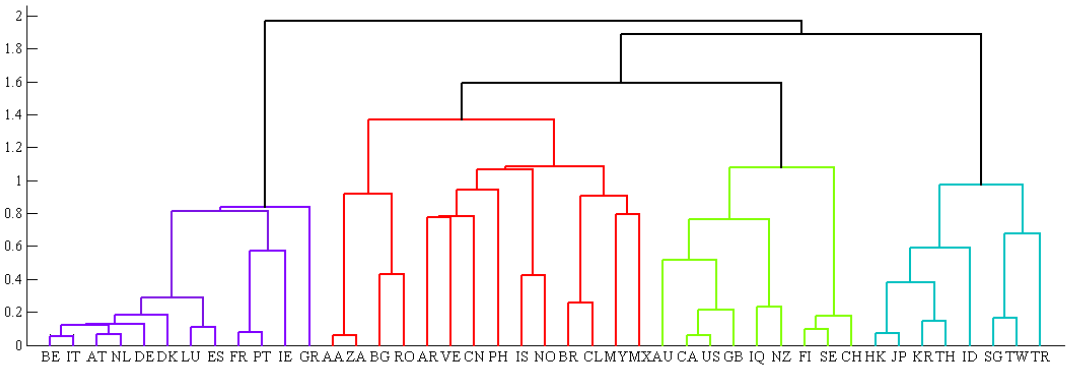
Figure 4: Break in global time-varying synchronization



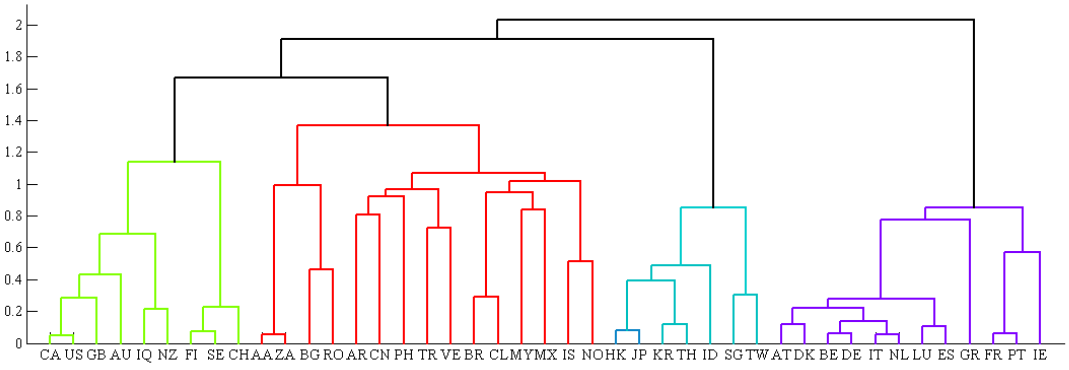
Note: Charts on the left show CUSUM tests for the global interdependence indexes. Charts on the right show the inferences regarding phase changes for the global interdependence indexes. The sample period is 1981:Q1-2013:Q2.

Figure 5: Hierarchical clustering from business cycle interdependence

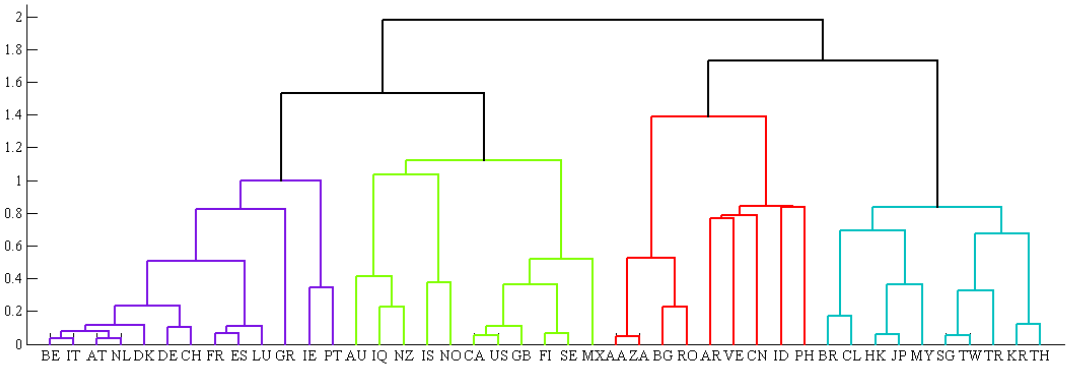
1981-2013



1981-2002

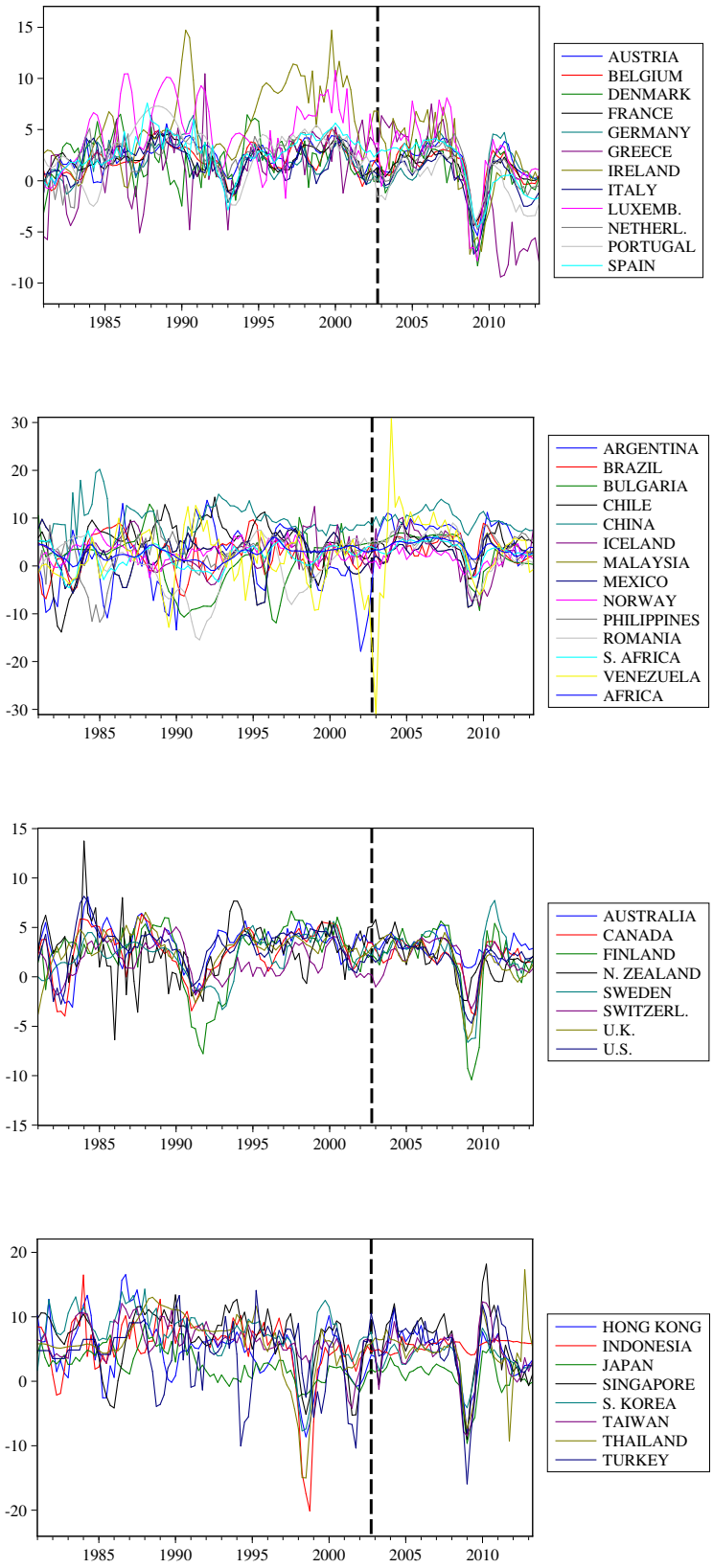


2003-2013



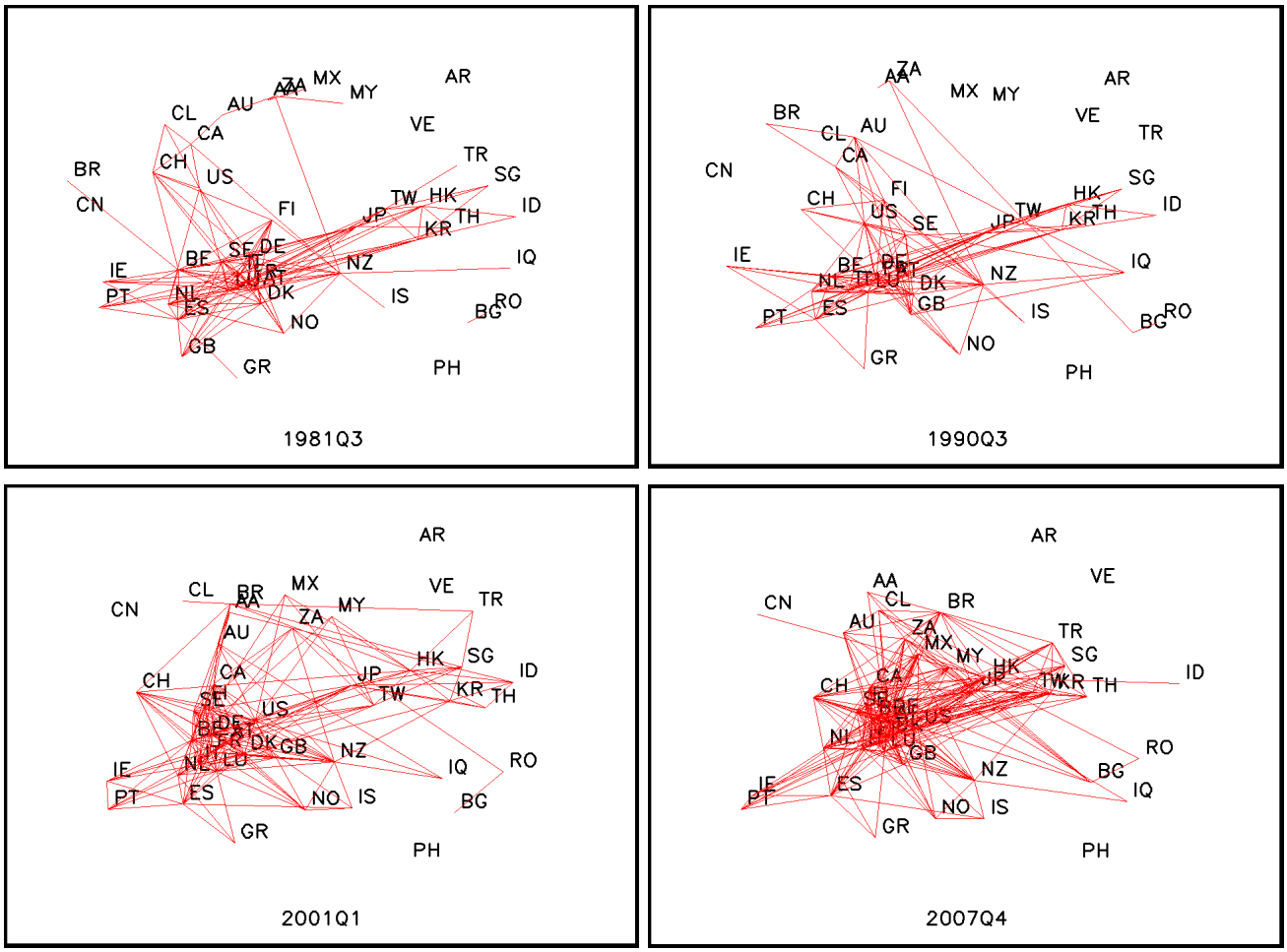
Note: The length of the dendrograms represents the level of dissimilarity at which observations or clusters are merged. Different colors represent different clusters based on a given level of dissimilarity.

Figure 6: Real GDP growth of major world economies classified by clusters



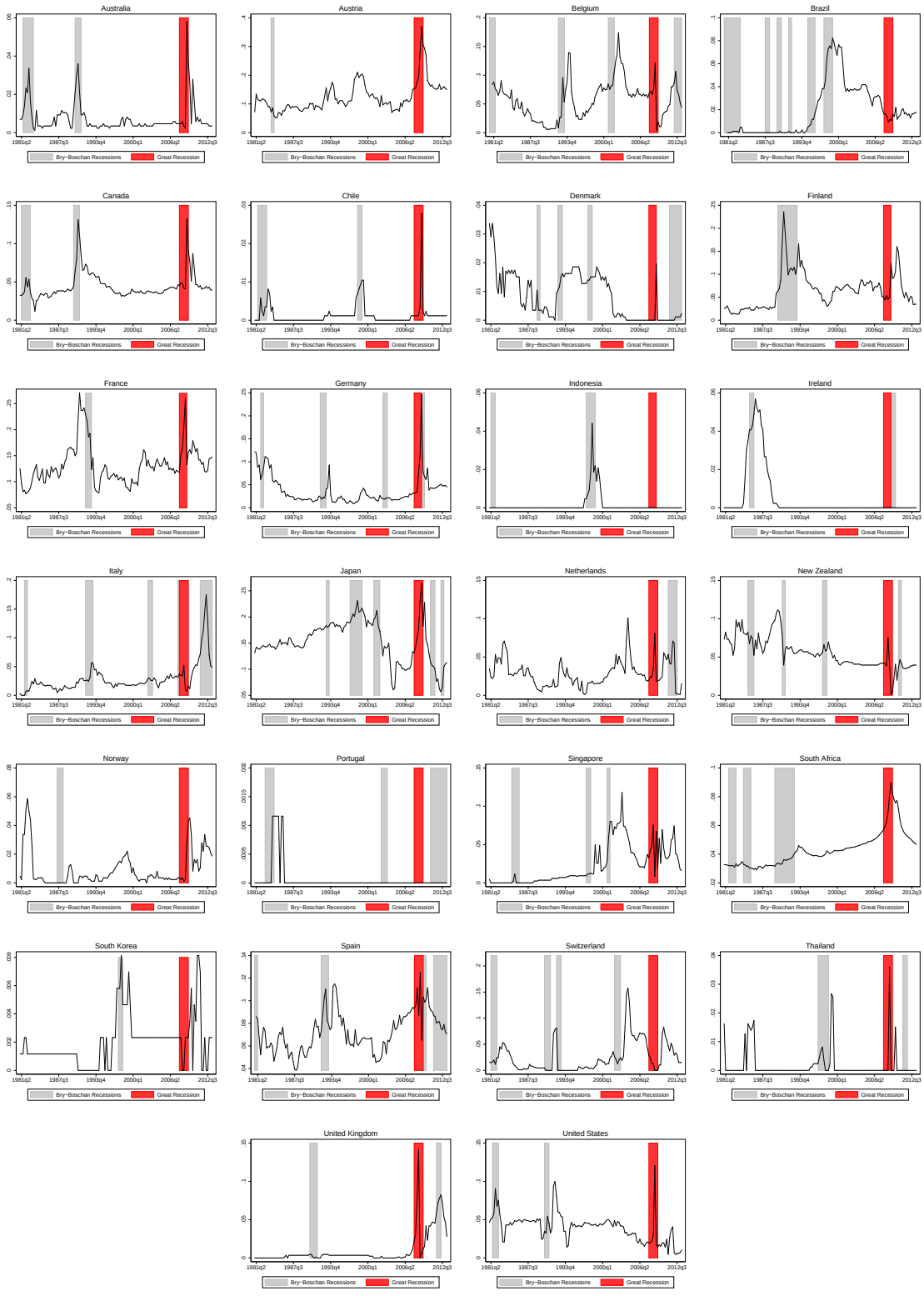
Note: Each chart contains the real GDP growth of countries in each of the cluster defined in Figure 5. Vertical line at 2002:Q4. Iraq is omitted in the figure because it experiences significantly greater fluctuation in real GDP growth because of its oil component. The sample period is 1981:Q1-2013:Q2.

Figure 7: World business cycle synchronization network



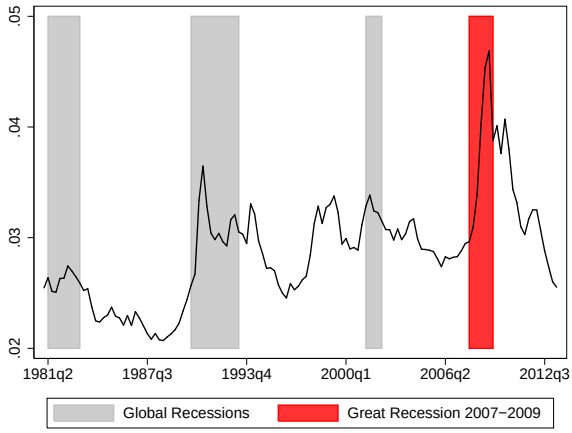
Note: The figure shows dynamic multidimensional scaling maps based on the distance between the business cycles of 43 developed and developing countries across periods of global recessions, as dated by the IMF: 1981 quarter 3, 1990 quarter 3, 2001 quarter 1, and 2007 quarter 4. The closer two countries 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 8: Betweenness centrality of countries



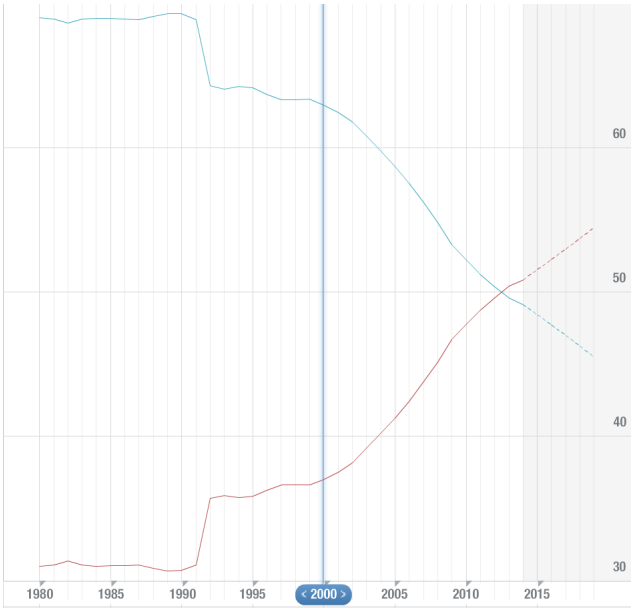
Note: Each chart plots the betweenness centrality for each country in the world business cycle synchronization network. The grey bars denote recessions identified by using the Bry-Boschan algorithm, and the red bar, the Great Recession of 2007-2009.

Figure 9: 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 10: GDP based on PPP, share of world



Note: The blue line plots the share of world GDP that corresponds to advanced economies. The red line plots the share of world GDP that corresponds to emerging market and developing economies. The shaded area represents the forecasted period. The source of the figure and the definitions of advanced economies and emerging market and developing economies correspond to the World Economic Outlook (April 2014) of the IMF: *http://www.imf.org/external/datamapper/index.php*