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Advanced Economies and Emerging Markets: Dissecting the Drivers of Business Cycle Synchronization

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Abstract

What are the divers of business cycle synchronization within and between advanced and emerging economies at the sector level? This question is addressed by analysing international co-movements of value added growth in a multi-sector dynamic factor model. The model contains a world factor, region factors, sector factors, country factors, and idiosyncratic components. The model is estimated using Bayesian methods for 9 disaggregated sectors in 5 developed economies (G5) and 19 emerging economies for the 1972-2009 period. The results suggest that, while there exists a common 'regional business cycle' in the G5, fluctuations in sectoral value added growth are dominated by country-specific factors in the emerging markets. Despite that, the international factor (the sum of world and sector factors) is more important than the region factor, suggesting that the emerging markets are more synchronized with the G5. A simple regression shows that (i) the world factor would be more important the larger the share of agriculture in output; (ii) in more open economies the sector factor is more important in explaining sectoral VA growth fluctuations; (iii) the region factors is more important the richer and the less volatile the economy. Finally, a comparison of the variance of sectoral value added growth accounted for by each factor from the pre- to the post-globalization period shows convergence of the business cycles within the G5 and EM, respectively. The changes in the contribution of the world, sector and region factor are due to changes in the importance of those factors within sectors. However, for the emerging markets, the fall in the importance of the country factors is dominated by changes in the structural composition of the economies. Therefore, the evolution of the structural composition in the emerging markets could be an important driver for more synchronized business cycles at the regional and international level.

Keywords: dynamic factors, disaggregated business cycles, international co-movement, emerging markets.
JEL Classification: C38, E32, F44.

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1. Introduction

The global economy has seen ample shifts since the mid-1980s. Emerging markets (EM) faced a process of increased trade and financial integration with the world and are gradually becoming major players. Has this process led to higher business cycle (BC) synchronization within EM and across the world? Given the increasingly integrated role of the EM and their increased share in the world economic growth, understanding the dynamics of BC in EM and dissecting the drivers of their co-movements has become a priority for policy-makers and international organizations, such as the World Bank and the IMF. As explained in World Bank (2016), since 2010, EM have displayed a synchronous slowdown in growth which could have significant spillovers on the rest of the world through not only trade and financial linkages but also through the confidence channel. Whether increased integration in trade and finance has led to more synchronized BC within EM and between EM and advanced economies remains an important empirical question. Economic theory provides only nuanced guidance about the impact of greater international linkages on output co-movement across countries. On the one hand, theory suggests that higher bilateral trade between country pairs is associated with more correlated BC. On the other hand, it suggests that if trade increases specialization and if industry-specific shocks are dominant, the degree of BC co-movement should decrease as trade linkages strengthen.

In this paper, we examine the dynamics of BC co-movements over time in a multi-sector and multi-country setting to provide an empirical characterization of common business cycle linkages at a disaggregate level among the EM and the advanced economies. We address the following questions. Firstly, what are the major factors driving BC synchronization in advanced economies and EM at the sector level? Second, what is the relationship between economic structural characteristics and the role of each dynamic factor in explaining VA growth volatility? Third, has the globalization period led to increased BC synchronization? Fourthly, are structural changes accountable for changes in the importance of these factors? This study will shed light on the ever growing debate on the two opposing views about whether international BC are converging or decoupling.

We address these questions by estimating common components for Value Added (VA) growth for 9 sectors of 5 advanced economies, namely, the US, France, Italy, Japan and the UK, (*hereafter*, the G5)[1] and 19 EM for the period covering 1972 to 2009, using the Groningen Growth and Development Centre (GGDC) dataset. A Bayesian dynamic latent factor model is estimated that comprises of a world factor, common to all sectors in all countries; a region factor, common to all sectors and countries in a given region; a sector factor, common to the same sector across all countries; a country factor, common to all sectors within the same country; and, an idiosyncratic term specific to each sector time series. This model will also be estimated for 2 sub-samples (pre- and post-1990) to evaluate the implications of globalization.

This study dissects the drivers of the G5 and the EM BC synchronization and examines the dynamics of those factors. Our results support the existence of a common 'regional BC' at the disaggregate level for the G5 but not for the EM. For the latter group of countries, it is the county factor that is found to account for the largest sectoral VA growth variability. Despite that, the international factor (the sum of world and sector factors) is more important than the region factor, providing evidence for the BC of EM being more synchronized with the 'world business cycle'. Moreover, the sectoral analysis of the variance decomposition suggests that international factors play a more important role in explaining fluctuations in VA growth in sectors that are tradeable. Further, our simple regression analysis demonstrates that (i) the world factor would be more important the larger the share of agriculture in output; (ii) in more open economies the sector factor is more important in explaining sectoral VA growth fluctuations; (iii) the region factors is more important the richer and the less volatile the economy. Then, when looking at the dynamics of international business cycles from the pre- to the post-globalization

[1] The GGDC dataset doesn't have sectoral data for Canada and only has data for West Germany. This is why we restrict our study to 5 out of the G7 economies.

period, we find that the BC of the G5 and the EM have substantially converged within their respective regions. For the EM, this result is driven by the BICS, implying that downturns in BICS could lead to more and more synchronous recessions in other EM. Finally, the variance decomposition changes in the contribution of the world, sector and region factor from the pre- to the post-globalization period are due to changes in the importance of those factors within sectors (i.e., the 'within effect'). However, for the EM, the fall in the importance of the country factors is dominated by changes in the structural composition of the economies and this effect also dominates for the change in the sector factor of the BICS. Therefore, the evolution of the structural composition in the EM could be an important driver for more synchronized business cycles at the regional and international level.

The rest of the paper is organized as follows. Next section presents the literature review. Section 3 describes the empirical methodology. In section 4, we provide a description of the data. Section 5 presents and discusses the empirical results. Section 6 presents the results for the pre- and globalization period and the sources of changes. Finally, we conclude this study in Section 7.

2. Literature Review

A large body of both theoretical and empirical literature can be related to our study. A number of studies have examined the role of trade and financial linkages on BC synchronization. For instance, trade was placed at the centrum of international BC spillovers by Frankel and Rose (1998) who established that that country pairs that increase bilateral trade are also displaying more correlated BC. Baxter and Kouparitsas (2005) also argue that the most important channel for BC co-movement is international trade. However, Imbs (2004) attributes co-movement to the correlation of shocks between countries. He argues that two countries with similar production structures will face greater BC co-movement if individual industries are subject to common shocks. [2] On the other hand, economic theory suggests that if trade increases specialization and if industry-specific shocks are dominant, the degree of output co-movement should fall with increased trade integration.

Many studies make use of dynamic factor models to quantify the importance of common factors in driving BC synchronization. Kose et al. (2003) estimate a dynamic factor model using Bayesian approach to examine the co-movements of output, consumption, and investment across countries, regions, and the world for the 1960-1992 period for a 60-country panel.[3] Their results provide evidence for the existence of a world BC. Using a high level of disaggregated data (117 sectors) for the US economy, Foerster et al. (2011) analyze co-movements in industrial production. Their results point to the common factor as the main driver of industrial production variability. Moreover, they show that the importance of the common factor fell during the Great Moderation period. Closer to our study, World Bank (2016) use a dynamic factor model for a sample of 106 countries (including advanced, emerging, frontiers and other developing markets) to decompose BC co-movements into global, group-, and country-specific factors. Their results suggest that the common EM-frontier factor accounts for about ¼ of the variation in growth in the emerging and frontier economies during the globalization period; it accounted half of that in the pre-globalization period.[4]

While the theoretical literature on international business cycles has emphasized the role of common country-level shocks and trade linkages in explaining business cycles co-movement, Long and Plosser (1983), stressed the importance of sectors and firms in the transmission of shocks in disaggregated BC

[2] For further studies on the role of trade and financial integration on the nature of BC see, Backus et al. (1995), Clark and van Wincoop (2001), Calderón et al. (2007), Burstein et al. (2008) and di Giovanni and Levchenko (2010).

[3] For other works using a Bayesian approach to dynamic factors to quantify international business cycles co-movements at an aggregate level, see Crucini et al. (2011), Kose et al. (2008), Kose et al. (2012), and Hirata et al. (2013).

[4] For a review of empirical estimates of spillovers from EM, see World Bank (20016), Annex 3.3.

models.[5] More recently, Gabaix (2011) shows that sectors or firms are linked to aggregate fluctuations because the size distribution is fat-tailed (known as the 'granularity' hypothesis) and therefore idiosyncratic shocks do not average out. Moreover, Acemoglu et al. (2012) suggest that idiosyncratic shocks to one sector that has strong 'input-output' linkages with other sectors, can have aggregate effects. Di Giovanni and Levchenko (2010) test the importance of input-output trade linkages in explaining international co-movement at the disaggregate level. Their results point towards increased aggregate co-movement due to vertical linkages (i.e. sectors that use each other as intermediates). This literature motivates the importance in understanding the role of sector-specific factors in international BC synchronization. Despite that, only a few papers examine the role of sector-specific factors at an international level. Exceptions are Costello (1993), Norrbin and Schlagenhauf (1996) and Karadimitropoulou and Leon-Ledesma (2013). We follow closely the empirical methodology of Karadimitropoulou and Leon-Ledesma (2013). They make use of a multi-sector multi-country dynamic factor model for 30 industries of the G7 economies for the 1974-2004 period. Sectoral VA growth is decomposed into four factors i) a 'world factor', capturing events that are common to all industries in all G7 countries; ii) a 'sector-specific factor', common to the same industry across all G7 countries; iii) a 'country factor', common to all industries within the same country; iv) an 'idiosyncratic component', specific to each individual industry. Their results suggest that while the country factor drives most of the fluctuations in industrial VA growth, the sector-specific factor is the second most important, while the world factor plays a negligible role. As they explain, when using aggregate data, the world factor captures both the factor common to all countries and industries and the factor common to the same industry across countries. By summing the percentage of the variability accounted for by those two factors, their results also support the existence of an 'international BC'.

This paper extends the empirical research on BC co-movements in several directions. Firstly, to our knowledge, no papers has examined the importance of sector-specific factors for the business cycles of the EM. The Bayesian approach to multiple dynamic factor models allows us to work with a large number of cross-sectional units and factors. Secondly, we augment the multi-sector dynamic factor model setting of Karadimitropoulou and Leon-Ledesma (2013) with a region specific factor, which enables us to combine both drivers previously found to be important in explaining BC synchronization, the region-specific factors and the sector-specific factors. Thirdly, we make use of a detailed level of disaggregation that also includes all major sectors in the sample countries. As shown in Karadimitropoulou and Leon-Ledesma (2013), the level of disaggregation is important as aggregated data could hide the role of sector-specific shocks and lead to a mischaracterization of commonality by overestimating the role of the world factor, especially if sectors have similar production structures as argued by Imbs (2004). Fourthly, our data span covers the period of globalization characterized by increased trade and financial integration both within the EM as well as with the rest of the world. We therefore split the data into two sub-samples and estimate the model for the pre-globalization and the globalization periods. This enables us to disentangle the sources of changes in BC co-movement at a disaggregate level into structural changes, changes in the importance of the factors within sectors, or an interaction between the two.

3. Empirical methodology

The specification and estimation method used draws from Karadimitropoulou and Leon-Ledesma (2013), which adapted the multi-factor dynamic model of Kose et al. (2003) to a multi-sector setting.[6] We adapt their model to our factor structure, which we augment with a region-specific factor to capture sectoral synchronization at a regional level.

[5] Foerster et al. (2011) have shown that these models can have an approximate dynamic factor representation like the one used in this study.

[6] We refer the reader to Kose et al. (2003) and Otrok and Whiteman (1998) for more details. Kose et al. (2003) approach extends the single dynamic factor model of Otrok and Whiteman (1998) to a multi-factor setting.

Our model contains i) a world factor, which is a factor common to all countries and sectors in the system; ii) a regional factor, which is common to all sectors and countries in a given region; iii) a sector factor, which is common to the same sector across countries; iv) a country factor, common to all sectors within the same country, and v) an idiosyncratic component. We obtained data for VA growth from the GGDC dataset for 9 sectors for the G5 and 19 EM plus the aggregate industrial VA growth for each of the economies from 1972 to 2009.[7] Following Kose et al. (2003), both the factors and the idiosyncratic components follow an AR(3) autoregressive process which captures the dynamic relationships in the model. Given the annual frequency of our data, this lag length should capture most spillovers (lagged or contemporaneous) across sectors and countries.

Consider a panel of sectoral VA growth rate series, $Y_{i,j,t}$, where the subscript i indexes the sector, with $i = 1,\ldots,I$, j indexes the country, with $j = 1,\ldots,J$, and $t = 1,\ldots,T$ indexes time. We assume that $Y_{i,j,t}$ can be described by the following dynamic factor model:

$$Y_{i,j,t} = \beta_{i,j}^{W} F_t^{W} + \beta_{i,j}^{R} F_{r,t}^{R} + \beta_{i,j}^{S} F_{i,t}^{S} + \beta_{i,j}^{C} F_{j,t}^{C} + \varepsilon_{i,j,t}\ , \tag{1}$$

where F^W represents the world factor, F^R is the region factor where r denotes the number of regions, F^s denotes the sector-specific factor, and F^c corresponds to the country-specific factor. Coefficients $\beta^W, \beta^R, \beta^S$, and β^C are the factor loadings on the world, region-, sector-, and country-specific factors, respectively. $\varepsilon_{i,j,t}$ is the idiosyncratic term that can be serially correlated but is assumed to be uncorrelated cross-sectionally at all leads and lags. This term follows an autoregressive process of order p (3 in our case):

$$\varepsilon_{i,j,t} = \sum_{l=1}^{p} \varphi_{i,j,l}\varepsilon_{i,j,t-l} + e_{i,j,t}, \tag{2}$$

where $e_{i,j,t}$ are distributed as $N(0, \sigma_{i,j}^2)$. The three unobserved factors F^{EM}, F^s, and F^c also follow an AR(3) process:

$$F_t^W = \sum_{l=1}^{p} \varphi_l^W F_{t-l}^W + \nu_t^W, \tag{3}$$

$$F_{r,t}^R = \sum_{l=1}^{p} \varphi_{r,l}^R F_{r,t-l}^R + \nu_{r,t}^R, \tag{4}$$

$$F_{i,t}^S = \sum_{l=1}^{p} \varphi_{i,l}^S F_{i,t-l}^S + \nu_{i,t}^S, \tag{5}$$

$$F_{j,t}^C = \sum_{l=1}^{p} \varphi_{j,l}^C F_{j,t-l}^C + \nu_{j,t}^C, \tag{6}$$

where $\nu_t^W, \nu_{r,t}^R, \nu_{i,t}^s, \nu_{j,t}^c \sim N(0,\sigma_W^2), N(0,\sigma_{r,R}^2), N(0,\sigma_{i,S}^2)$, and $N(0,\sigma_{j,C}^2)$ respectively. Finally, the innovations, $e_{i,j,t}$ and $\nu_t^W, \nu_{r,t}^R, \nu_{i,t}^S, \nu_{j,t}^C$, are mutually orthogonal across all equations in the system.

As explained in Kose et al. (2003), this 6-equations model suffers from rotational indeterminacy and faces two related identification problems, as the signs and the scales of the factors and their loadings cannot be separately identified. By restricting one of the factor loadings to be positive for each of our four factors, we can resolve the identification problem of the signs. We therefore restrict the factor loading for (1) the world factor to be positive for the aggregate industrial VA growth rate series of the first country in the dataset, namely the US; (2) the region factor to be positive for the aggregate industrial VA growth rate series of the first country in each region, namely the US for the G5 region factor and China for the EM region factor; (3) the sectoral factors to load positively for all sectors of the first country in the dataset; (4) the country factors to load positively for the aggregate variable of each country.

[7] The aggregate is only used for identification purposes.

Finally, we overcome the identification issue of the scales by assuming that each $\sigma_W^2, \sigma_{r,R}^2, \sigma_{i,S}^2$ and $\sigma_{j,C}^2$ are constant.

Equations (1) to (6) are estimated using the Bayesian approach with Gibbs sampling techniques. Gibbs sampling is a Markov Chain Monte Carlo (MCMC) method which approximates joint and marginal distributions by sampling from conditional distributions.[8] In this study, given that the full set of conditional distributions (that is, parameters given data and factors, and factors given data and parameters) are known, we can make use of the MCMC procedure which enables us to generate random samples for the unknown parameters and the unobserved factors from the joint posterior distribution. In particular, the algorithm can be summarized by the following steps:

1. Conditional on a draw for F^W, F^R , F^s, and F^c, we simulate the AR coefficients and the variance of the shocks to equations (2), (3), (4), (5), and (6).
2. Conditional on a draw of F^W, F^R , F^s, and F^c, we draw the factor loadings $\beta^W, \beta^R, \beta^S, and\ \beta^C$.
3. Simulate F^W, F^R , F^s, and F^c conditional on all other parameters above.

The sample produced is the realization of one step of the Markov-Chain. We then repeat this process to generate drawings for the regression parameters and the factors at each step.

While our methodology does not allow us to identify the structural shocks driving these factors, we follow Karadimitropoulou and Leon-Ledesma (2013) who make use of economic theory and provide a number of possible interpretations of these factors. The world factor could be capturing advanced economies and EM common demand and supply shocks, including common policy shocks, or sector-specific shocks that become common to all countries when transmitted through international inter-sectoral linkages, as explained in Acemoglu et al. (2012). They could also capture external shocks that affect all sectors and all countries in our sample. Similarly, the region factor could be capturing region-specific common demand and supply shocks. The country factors could be capturing macroeconomic shocks affecting all sectors of a given country or sectoral-specific shocks that are transmitted through national input-output linkages as in Foerster et al. (2011). The sectoral factors could be capturing sector-specific demand and cost shocks or sectoral shocks that are transmitted through international intra-sectoral linkages.

We then present our results using variance decompositions by estimating the relative contributions of the different factors to the variance of VA fluctuations for each individual sector. More precisely, the variance of $Y_{i,j,t}$$Y_t^{i,j,k}$, with orthogonal factors is given by:

$$var(Y_{i,j,t}) = (\beta_{i,j}^W)^2 var(F_t^W) + (\beta_{i,j}^R)^2 var(F_{r,t}^R) + (\beta_{i,j}^S)^2 var(F_{i,t}^S) + (\beta_{i,j}^C)^2 var(F_{j,t}^C) + var(\varepsilon_{i,j,t}). \quad (7)$$

The variance of each sectoral VA growth rate series, $Y_{i,j,t}$, can be decomposed into the fraction due to i) the world factor, ii) the region-specific factor; iii) the sector-specific factor, and iv) the country-specific factor. We compute the fraction of fluctuations due to each of our four factors, represented by $f = W, R, S, C$ as:

$$\frac{(\beta_{i,j}^f)^2 var(F^f)}{var(Y_{i,j,t})}. \quad (8)$$

Measures of equation (7) and (8) are obtained at each step of the Markov-Chain.

Given the dimension of our dataset (24 countries, *J=24*, 9 sectors, *I=9*, thus 216 VA growth rate series, *IJ=216*), for presentational issues, we present the relative importance of the factors at the country level. In particular, we condense the results by aggregating $var(Y_{i,j,t})$ into an aggregate forecast error over sectors.[9] To do so, we build a $(J \times I)$ matrix of VA weights W_J. The variance matrix is then reduced to *J* country variance decompositions by multiplying (7) times W_J'.

[8] More technical details on Gibbs sampling can be found in Chibb and Greenberg (1996) and Geweke (1996).
[9] In the aggregation process, the aggregate VA series is ignored, so that sectors weights sum up to one.

4. Data

Our data come from the GGDC 10-Sector Database which covers annual macroeconomic data series for 10 broad sectors for 13 countries in Africa, 11 countries in Asia, and 9 in Latin America, 8 European countries and the U.S. The GGDC dataset has the advantage of covering a wide sample of EM at a disaggregate level, that covers all of the economy.[10]

We select our data based on availability. We make use of 9 sectors for the G5 and 19 EM from 1972 to 2009.[11] Data were missing for the Government Services sector for some of the sample countries. We only include in our sample those countries for which data are available for the 1972-2009 period, which enables us to estimate the model for two sub-samples, namely, the pre-globalization and the globalization periods.[12] Our data cover all of the economy, including Agriculture, Hunting, Forestry and Fishing; Mining and Quarrying; Manufacturing; Electricity, Gas and Water Supply; Construction; Wholesale, Retail Trade, Hotels and Restaurants; Transport, Storage and Communication; Finance, Insurance, Real Estate, and Business Services; and, Community, Social and Personal Services.[13] Each series was log first-differenced and demeaned. For the models estimated for the pre-globalization and the globalization periods, T = 19, respectively.

As previously outlined, both the factors and the error term follow an AR(3) process. The prior on all the factor loadings is $N(0,1)$, while the one for the autoregressive polynomial parameters is $N(0,\Sigma)$, where $\Sigma = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0.5 & 0 \\ 0 & 0 & 0.25 \end{bmatrix}$. The prior on the innovation variances in the observable equations is Inverted Gamma (6, 0.001), which is quite diffuse, as in Kose et al. (2003).

Finally, Kose et al. (2012) explain that it is essential to monitor the convergence of the Markov chain since we are not sampling from the posterior itself as the elements of the Markov chain are converging to drawings from the posterior. The results remained quantitatively similar same using chains of different lengths ranging from 5,000 to 21,000. The analysis presented in the next section is based on 21,000 Gibbs sampling replications, from which the first 1,000 are discarded as burn-in. Therefore, the results are from the remaining 20,000 iterations.

5. Results

5.1. Factors and correlations

Figure 1 plots the world factor (solid line) and the 33 and 66 percent quantile bands (dotted lines). The tightness of the bands demonstrates that the factor is precisely estimated. Importantly, it captures some major global events: the first and second oil crises of 1974-75 and 1979, and the dotcom bubble collapse in 2000-01. The region factors also display other significant downturns that were specific to the G5 and the EM, respectively. For the G5, the factor displays the growth associated with the technology boom in the late 1990s and the subsequent burst of the dotcom bubble as well as the 2007 Global Financial crisis. The EM factor captures the Latin American debt crisis of the early 1980s, the 1994 Mexican crisis, the Asian crisis of 1997-98, the Argentinian crisis of 2001-02, as well as the Global Financial Crisis.[14] The world factor also captures the Great Moderation period that followed the turmoil

[10] For an analysis on the GGDC dataset and its advantages, see Timmer et al. (2015).

[11] Data is only available until 2009 for the G5 and 2010 for the EM, hence the choice of our sample period.

[12] Appendix A provides a list of the countries considered by region.

[13] Appendix B provides the list of the sectors and their corresponding ISIC rev.3.1. code.

[14] The fact that the Global Financial Crisis is not captured by the world component but is instead accounted for by both region factors could be due to the sample ending in 2009 and therefore a lack of data series to really capture the common dynamics across all sectors and countries across the world. It could also be pointing to different sectoral level effects across the two different regions as the aggregate sector-specific factor, which is what aggregate data studies capture in their world factor, is clearly capturing this common downturn.

economic environment of the 1970s and 1980s. This is also reflected in Table 1, which shows a fall in the standard deviation of the world factor from 1.91% in the 1972-1990 period to 0.78% in the 1991-2009 period. All other factors also display a fall in the standard deviation, except from the G5 region-specific factor due to the high growth that preceded the dotcom bubble burst. Averaging the standard deviations of the country factors for the EM and the G5 separately across the two-periods suggests that the observed fall is driven by the EM, while that of the G5 actually increased.

Figure 3 presents the evolution of (1) the aggregate VA growth for selected countries, (2) the international (world plus sector) factor, (3) the region factor, and (4) the country factor. We make the scales of the factors and VA growth comparable by multiplying the world, region, sector, and country factors by the estimated factor loadings (median of the MCMC chain). We present the graphs for the G5 and the BICS countries (i.e, Brazil, India, China and South Africa), which is a good representation of the three different continents in the EM sample. Clearly, for the BICS, the country factors appear to co-move strongly with aggregate growth. This is not the case for the international and region factors.[15] This pattern is similar across all EM. For the G5 economies on the other hand, while the respective VA growths and country factors display a high co-movement, the other two factors also seem to play a non-negligible role. In particular, the international factor seems to commove with the VA growth of the G5 at the beginning of the sample period, while the region factor is more important towards the end of the sample. We would therefore expect, decoupling of the G5 economies from the world business cycle and convergence with the regional business cycle.

Table 2 presents the average correlations between the aggregate VA growth and the world factor, the region factor, the aggregate sector factor and the country factor for the G5 and the EM. Not surprisingly, on average, the world, sector and region factor display the highest correlations with the advanced economies, while the country factor is highly correlated with VA growth of EM.

5.2. Variance Decompositions

Table 5 presents the variance decomposition of VA growth explained by each factor. The results are aggregated at the country-level as previously explained, and display the median (50%) posterior quantile. Due to the large number of worldwide countries covered in our sample as well as the high level of disaggregation, idiosyncratic components are on average responsible for about 42% of the variation of industrial VA growth; this percentage differs substantially at the country-level. In particular, they seem to be more important in African countries. This implies that a large percentage of the variability of VA at the sector level is due to sector-specific shocks that are not transmitted either nationally or internationally and therefore affect specific sectors differently in different countries.

From the remaining three factors, in the G5 economies, the region factor explains the largest fraction of the fluctuations in industrial VA growth (25%) while the county factor follows very closely accounting for 24%. This points to the existence of a common G5 BC at the disaggregate level.[16] From the international component, the sector factor is more important than the world factor and this holds across all G5 counties.[17] This result is consistent with Karadimitropoulou and Leon-Ledesma (2013), who suggest that the sector-specific factor is more important in explaining international BC co-movement than

[15] We also drew graphs where the international factors are decomposed into their two components, the common and the sector factors. Those graphs are available upon request.

[16] For evidence on the existence of a common BC for developed countries, see, for instance, aggregate data studies by Kose et al. (2003), Kose et al. (2008) and Kose et al. (2012). Using disaggregate data, Karadimitropoulou and Leon-Ledesma (2013) show that when the proportion of the variance explained by world and industry factors is added up, the results support the prominence of "international" over "country-specific" factors, concluding for a "G7 business cycle".

[17] For robustness, keeping the structure of the dataset the same, we estimated a model with three factors including the world, sector and country factors. There is no quantitative difference in the percentage of the variance accounted for by the world and sector factors in the two models.

the world factor. For the EM, the country factor dominates, explaining the largest fraction of the fluctuations in industrial VA growth for all countries. As expected from the evidence in Figure 2, while the world factor plays a negligible role in driving fluctuations in VA growth, the sector-specific factors account for a larger percentage of variability. Importantly, sector factors are the second most important drivers of sectoral output growth for 12 out of 19 EM. They explain an economically significant fraction of around 9%. While the world factor seems to play a smaller role (<5%) in 13 out of 19 countries, the sector-specific factors account for over 10% in 6 countries, and for a percentage between 5-10% for all the remaining countries, except Egypt and China. The region factor accounts on average for 7.5% of VA growth fluctuations in EM, suggesting that there is no evidence of a common EM BC at the disaggregate level. These results are in line with the evidence provided in Kose et al. (2012) for EM business cycles at the aggregate level. Finally, when looking at the sum of the world and sectoral factors (the international factor) for each country, this percentage is still less important than the country factor for all countries, except Nigeria.[18] Interestingly however, while for the G5 the region factor remains more important than the international factor, the opposite pattern is observed for the EM. This implies that the BC of a given EM is more synchronized with that of a developed country than that of another EM.

Given the large number of dimensionality in our data, it is not possible to show the variance decomposition for each sector of each country.[19] Figure 4 shows the percentage of sectoral VA variance accounted for by each factor at the country-level. Those histograms further illustrate the above points. For the majority of the G5 the region factor explains a significant amount of sectoral VA growth volatility. The country factor is particularly important for EM. The sector factor seems to be more important than the world factor in explaining sectoral VA growth fluctuations, but there doesn't seem to be a significant difference between G5 and EM.

Appendix C shows the percentage of the explained part of the variance accounted for by each factor (at the sector-level). The "explained" part of the variance, which is the part not accounted for by idiosyncratic components, is useful to obtain comparable magnitudes of the relative importance of each factor. Looking at the first block of rows, we can see that the world factor accounts between 30-60% of the sectoral VA growth variance for 37% of the countries in sector 1 (Agriculture, Hunting, Forestry, and Fishing) and 29% of the countries in sector 2 (Mining and Quarrying). The sector factor accounts for over 20% of the explained part of the variance for a majority of countries in Mining and Quarrying, Manufacturing, and Electricity, Gas, and Water Supply sectors. This latter sector also displays large part of their variances being explained by the region factor, accounting for over 50% in ¼ of the countries. Moreover, Transport, Storage and Communication (sector 7), and Finance, Insurance, Real Estate and Business Services (sector 8) seem to display an important region-specific component in their VA growth fluctuations. This result points to the difference of technological and financial developments between the G5 and the EM. Finally, the country factor seems to be more important for sectors 5-9 in a large majority of the counties. Not surprisingly, the results point out that international factors play a more important role in explaining fluctuations in VA growth in sectors that are more tradable. This result is in line with the conclusions drawn in Karadimitropoulou and Leon-Ledesma (2013) for the G7 economies. Importantly, the factor loadings on the world, sector, and region factor are positive for the aggregate sector of all countries. Given that the world and the sector factors are identified by a positive factor loading for the US aggregate VA growth, this implies that what is good for the US is good for the rest of the counties. The region factors are identified by a positive factor loading for the aggregate VA growth of

[18] Note that for Nigeria, while the 'international component' dominates the country-specific factor, the idiosyncratic component in the country is the largest amongst the sample countries. Thus overall, at the sector level Nigeria faces very idiosyncratic sector-specific BCs.

[19] Due to the lack of exchange rate data for some EM in our sample, we would have needed to lose a large part of our time dimension to aggregate the variance decomposition results at the sectoral level.

the US and China, for the G5 and EM regions respectively. Thus, on aggregate, what is good for the US is good for the remaining developed countries, while what is good for China is good for all the EM. [20]

5.3. Dynamic Factors, Variance Decomposition and Economic Structural Characteristics

In an effort to uncover the relationship between economic structural characteristics and the role of each dynamic factor in explaining VA growth volatility, we employ some simple regression analysis. In particular, we regress the median of the posterior quantiles of the variance proportions explained by the world, sector, region and country factors on (i) the average ratio of per capita GDP to U.S. per capita GDP (*PCGDP*), (ii) openness measured by trade as a percentage of GDP (*Trade*), (iii) agriculture's share of output (*AGR*), and (iv) manufacture's imports as a percentage of merchandise imports (*MANFM*), and (v) VA growth volatility (*VAVOL*). [21] Results are presented in Table 4 and are useful in drawing regularities that could merit further study.

When interpreting the results for the world factor, one needs to keep in mind that it explains a very small fraction of VA growth variance in both the G5 and the EM and the difference between the two groups of countries is marginal (3.66% for the G5 vs 4.10% for the EM). Despite that the regression suggests that this factor would be more important the larger the share of agriculture in output, which is naturally the case for the EM. The coefficient on trade in the regression using the sector factor variance decomposition is significant and positive, indicating that in more open economies, the sector factor is more important in explaining sectoral VA growth fluctuations. International intra-sectoral linkages could be important drivers of sectoral factors and this goes in line with the results in Karadimitropoulou and Leon-Ledesma (2013) who found their measure of openness at the sectoral-level to be correlated with their industry factor. The regional factor is more important the richer the economy and the less volatile the economy. This is consistent with the finding in Table 3 that the region factor is more important in explaining sectoral VA growth fluctuations in the G5, that is the developed economies with higher levels of income and less volatile VA fluctuations. Finally, all those structural characteristics seem to explain the cross-country differences in the variance proportions explained by the country factor. Importantly, the sign of the coefficients is the opposite of what was observed in the previous three regressions. Thus, poorer economies with larger VA growth fluctuations that are less open to trade will have a larger variance proportion explained by the country factor. The results also suggest that countries with higher relative size of agriculture sector will have a lower country factor. This is in line with the results in Table 3, as for instance, Nigeria, Kenya and Morocco are three of the top 5 economies with the largest agriculture sector and in the bottom 5 with the lowest country factor.[22]

[20] There are 960 factor loadings in total making it impossible for us to report the posterior distributions for each country and sector. Overall, there are 931 positive loadings and only 29 negative ones (25 of them across the EM and 4 in the G5).

[21] All economic structure variables come from the World Development Indicators of the World Bank. PCGDP is real GDP per capita in constant 2010 U.S. dollars; and VAVOL is the standard deviation of VA growth over our sample period. For Trade, AGR, and MANFM, we make use of the 2009 year data (final year of our sample), while for PCGDP we make use of the average ratio over our sample period. We have experimented with using different years (i.e., 2005 to have measures before the Global Financial Crisis) and the results remained quantitavely robust. We also experimented with different economic characteristic such as, terms of trade volatility, the government's expenditure share in GDP, manufacturing's share of output and ICT goods exports or imports as a percentage of total goods exports or imports. Those variables were insignificant for all dynamic factors.

[22] These results provide further explanation as to why Nigeria could be facing the highest proportion of its VA growth variance accounted for by the international factor. It is by far the county with the largest share of agriculture sector in output and is in the top tercile for trade.

6. From the Pre-Globalization to the Globalization period: the dynamics of international business cycles

6.1. Variance Decompositions: evolution of the importance of the factors

World Bank (2016) explains that the contribution of EM to global GDP is now more than one-and-a-half as much as it was in 1980. EM have also increased their share in the global economy with integration in international trade and finance, becoming major export destinations. Following this observation, we now address another important question: how did the importance of world, sector, region and country factors evolve as globalization deepened over the past two decades? In order to obtain comparable magnitudes of the relative importance of each factor, we examine changes in the "explained" part of the variance, that is, the part not accounted for by idiosyncratic components. The sample is split in two periods, the pre-globalization (1972-1990) and globalization (1991-2009) periods. While the sample split point is arbitrary, it coincides with the observation of increased integration of the EM with the rest of the world, and it also enables us to preserve sufficiently long time-series components either side. We then estimate a dynamic factor model and obtain the variance decomposition for each sample period.

Figure 5 presents the variance decomposition aggregated at the country-level (for the explained part) for each period. Each bar represents the cross-sectional mean of the variance (in %) attributable to the world, sector and region factor. We also show the "international factor", which is the sum of the world and sector factors. Several observations can be drawn from those results. Firstly, in both periods the international factor does not support the existence a 'global business cycle' as for both the G5 and the EM the international factor accounts for about ¼ of the sectoral VA variability. For the developed countries, the region-specific factor points towards the existence of a 'G5 business cycle' as it accounts for the largest percentage of VA growth variance. These results are in line with the hypothesis we drew from Figure 3, namely that the G5 are decoupling from the 'world business cycle' and are converging towards a 'regional business cycle'.

Secondly, the EM region-specific factor explained a small part of the variance of sectoral VA growth when EM were not well integrated with each other. Since the 1990s, the EM region-specific factor accounts for about 25% of the variability in sectoral growth, implying that a more pronounced EM BC has emerged over time. This result is mainly driven by the BICS economies for which the importance of this factor has more than doubled. Therefore, downturns in BICS could lead to synchronous recessions in other EM. These results are in line with the aggregate level analysis of the World Bank (2016) who draws the same conclusions.

Thirdly, the international factor is still more important than the EM region-specific factor for EM. This confirms the previous result that the sectoral BC of a given EM is more synchronized with that of a developed country than that of another EM. Moreover, we observe that the increase in the importance of the international factor for the EM is driven by the sectoral component. This suggests that sector-specific demand and cost shocks or sectoral shocks that are transmitted through *intra*-sectoral linkages are increasingly playing a more important role for the synchronisation of the international business cycle, and hence, the convergence of EM and developed economies.

6.2. Variance decomposition changes: a shift-share analysis

We now look further into the changes in the variance decomposition from the pre-globalisation to the globalisation period by performing a shift-share analysis to dissect the role of structural changes from the role of changes in the importance of the factors within sectors. This is done by decomposing changes in the variance decomposition of the world, sector, region, and country factors into three different effects, namely, a '*within effect*', a '*structural effect*', and an '*interaction term*'. More precisely, we compute the country-level fraction of fluctuations, VD_j^f, due to each of our four factors, f, by aggregating across all sectors i in each country, j, as shown below:

$$VD_j^f = \sum_i \left[S_{i,j} * VD_{i,j}^f \right] \tag{9}$$

where, $VD_{i,j}^f$ is the fraction of the variance decomposition of sector i in country j accounted for by each of our four factors, f; and $S_{i,j}$ is the share in VA of sector i in country j.

The change in the variance decomposition from the pre- to the post-globalisation period can then be decomposed as follows:

$$\Delta VD_j^f = \sum_i \left[S_{i,j,0} * \Delta VD_{i,j}^f + \Delta S_{i,j} * VD_{i,j,0}^f + \Delta S_{i,j} * \Delta VD_{i,j}^f \right] \tag{10}$$

where, 0 represents the pre-globalization period.

The first term of the right-hand side in (10) is the '*within effect*' which measures the contribution of post-globalisation variance decomposition changes at the sector-level accounted by each factor holding VA shares at their pre-globalization values. The second term, the '*structural effect*', holds the variance decompositions accounted by each factor at their pre-globalization values and measures the contribution of changes in sectoral VA shares between pre- and post-globalisation periods. The final term is the '*interaction effect*' and estimates the contribution arising from the co-movement between changes in both the sector-level variance decompositions and the structural composition.

Figure 6 shows the cross-sectional means of the contribution of each of the three effects for the G5, EM, the BICS and Non-BICS. For all groups of countries, the 'within effect' is very large and dominates positively for all factors, except the country factor. This implies that, for the world, sector and region factors, changes in the importance of the factors within sectors dominate the effect of changes in the structural composition of the economy. The other two effects play a minimal role across those three factors. The only exception to this is the importance of the structural effect in the variance decomposition changes of BICS accounted by the sector factor.[23] This negative effect suggests that there were important changes in the structural composition of those economies, mainly driven by China, India, and South Africa, which increased the share of tradeable sectors in VA growth. The interaction term accounts for a large fraction of the change in the variance decomposition accounted for by the world factor in the G5, while it contributes positively to BICS and negatively to non-BICS. When the contribution of this effect is positive, it demonstrates that, on average, sectors whose variance decomposition has gained (lost) importance have also gained (lost) shares. On the other hand, when it is negative, it shows that sectors whose variance decomposition has gained (lost) importance have lost (gained) shares. Finally, for the country factor, while the change is almost entirely accounted for by changes in the importance of the factor for the G5 economies, for the EM this change is dominated by changes in the structural composition, with the effect being more pronounced in the non-BICS economies. Hence, the evolution of the structural composition in the EM is reducing the importance of their country-level sectoral BC co-movement, giving way to more synchronized BC at both the regional and the international level.

5 Conclusions

This study provides an empirical examination of the importance of world, sector, region and country factors for the G5 and the EM BC co-movement in sectoral VA growth. A dynamic factor model is estimated using a Bayesian approach which decomposes sectoral VA growth into a world, region, sector, country, and an idiosyncratic component. We make use of the GGDC dataset for the G5 and 19 EM and 9 sectors for the 1972-2009 period.

[23] The percentage of sectoral VA growth variability accounted for by the sector factor increased from 6.58% to 10.93% for BICS from the pre- to the post-globalization period.

We dissect the drivers of BC synchronization between and within the G5 and EM and examine the dynamics of those factors. Firstly, we find support for the existence of a common 'regional BC' at the disaggregate level for the G5 but no for the EM. For the latter group of countries, while the county factor dominates, the international factor is more important than the region factor in explaining sectoral VA growth variability. This implies that the BC of EM is more synchronized with the 'world business cycle'. Secondly, the sectoral variance decomposition analysis shows that international factors play a more important role in explaining fluctuations in VA growth in sectors that are tradeable. Thirdly, our simple regression analysis demonstrates that (i) the world factor would be more important the larger the share of agriculture in output; (ii) in more open economies the sector factor is more important in explaining sectoral VA growth fluctuations; (iii) the region factors is more important the richer and the less volatile the economy. Fourthly, when looking at the dynamics of international business cycles from the pre- to the post-globalization period, we find that the business cycles of the G5 and the EM have substantially converged at their respective regions. For the EM, this result is driven by the BICS, implying that downturns in BICS could lead to more and more synchronous recessions in other EM. Despite that, the international factor is still more important than the EM region-specific factor and this is due to increases in the sector factor. Therefore, sectoral shocks that are transmitted through intra-sectoral linkages could be important drivers for the convergence of EM and advanced economies business cycles. Finally, the variance decomposition changes in the contribution of the world, sector and region factor from the pre- to the post-globalization period are due to changes in the importance of those factors within sectors (i.e., the 'within effect'). However, for the EM, the fall in the importance of the country factors is dominated by changes in the structural composition of the economies. Therefore, the evolution of the structural composition in the EM could be an important driver for more synchronized business cycles at the regional and international level.

Appendix A: List of Countries by Region

G5	Africa	Asia	Latin America
US	Egypt	China	Argentina
France	Kenya	India	Brazil
Italy	Mauritius	Indonesia	Chile
Japan	Morocco	Korea (Rep. of)	Colombia
UK	Nigeria	Malaysia	Mexico
	South Africa	Philippines	Peru
		Thailand	

Appendix B: List of Sectors

Sector Number	GGDC 10 Sector Database (ISIC rev. 3.1 code)	Sector
1	AtB	AGRICULTURE, HUNTING, FORESTRY AND FISHING
2	C	MINING AND QUARRYING
3	D	MANUFACTURING
4	E	ELECTRICITY, GAS AND WATER SUPPLY
5	F	CONSTRUCTION
6	GtH	WHOLESALE, RETAIL TRADE, HOTELS AND RESTAURANTS
7	I	TRANSPORT, STORAGE AND COMMUNICATION
8	JtK	FINANCE, INSURANCE, REAL ESTATE AND BUSINESS SERVICES
9	OtP	COMMUNITY, SOCIAL, AND PERSONAL SERVICES

Appendix C: Explained part of sectoral VA Variance at the sector-level due to the World, Sector, Region and Country Factors

	Sector								
Variance (%) due to WF	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
0	46	38	83	67	79	92	71	75	58
10	13	17	17	17	8	4	13	8	33
20	4	17	0	0	0	0	4	4	4
30	21	4	0	8	8	0	8	0	4
40	4	17	0	0	0	4	4	8	0
50	8	4	0	0	0	0	0	0	0
60	4	4	0	4	4	0	0	0	0
70	0	0	0	4	0	0	0	4	0
Variance (%) due to SF									
0	33	25	33	46	63	54	38	54	63
10	25	17	13	8	17	33	46	13	17
20	17	25	21	8	13	4	8	25	17
30	17	13	21	8	4	4	4	4	4
40	8	4	0	13	0	4	4	0	0
50	0	4	8	13	0	0	0	4	0
60	0	8	4	4	0	0	0	0	0
70	0	4	0	0	4	0	0	0	0
Variance (%) due to RF									
0	42	46	42	21	58	38	29	25	38
10	25	17	21	21	13	25	29	25	29
20	0	8	17	8	4	21	8	21	17
30	17	13	17	13	8	8	17	8	4
40	4	8	0	13	8	4	8	8	0
50	4	4	0	17	4	0	4	4	4
60	8	4	0	4	0	4	4	8	4
70	0	0	0	0	4	0	0	0	4
80	0	0	4	4	0	0	0	0	0
Variance (%) due to CF									
0	21	13	13	17	4	0	4	8	8
10	13	38	0	8	8	8	13	8	4
20	8	13	4	17	4	0	0	0	0
30	17	8	17	25	4	0	8	8	4
40	8	8	4	17	8	8	17	17	4
50	4	0	21	8	8	13	13	8	17
60	8	8	8	4	17	13	17	42	17
70	8	4	8	4	21	29	13	0	17
80	4	8	21	0	25	25	17	4	29
90	8	0	4	0	0	4	0	4	0

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References

Acemoglu, D., Carvalho, V.M., Ozdaglar, A., and Tahbaz-Salehi, A., 2012. The Network Origins of Aggregate Fluctuations. Econometrica 80, 1977-2016.

Backus, D.K., Kehoe, P.S., and Kydland, F.E., 1995. International Business Cycles: Theory and Evidence, in: Cooley, T.F. (Eds.), Frontiers of Business Cycle Research. Princeton, NJ: Princeton University Press, 331-357.

Baxter, M., and Kouparitsas, M.A., 2005. Determinants of Business Cycle Comovement: A Robust Analysis. Journal of Monetary Economics 52, 113-157.

Burstein, A., Kurz, C., and Tesar, L., 2008. Trade, Production Sharing, and the International Transmission of Business Cycles. Journal of Monetary Economics 55, 775-795.

Chib, S., and Greenberg, E., 1996. Markov Chain Monte Carlo Simulation Methods in Econometrics. Econometric Theory 12(3), 409-431.

Clark, T., and van Wincoop, E., 2001. Borders and Business Cycles. Journal of International Economics 55, 59-85.

Costello, D.M., 1993. A Cross-Country, Cross-Industry Comparison of Productivity Growth. Journal of Political Economy 101, 207-222.

Crucini, M.J., Kose, A., and Otrok, C., 2011. What are the Driving Forces of International Business Cycles. Review of Economic Dynamics 14, 156-175.

Di Giovanni, J., and Levchenko, A.A., 2010. Putting the Parts Together: Trade, Vertical Linkages, and Business Cycle Comovement. American Economic Journal: Macroeconomics 2, 95-124.

Foerster, A.T., Sarte, P.G., and Watson, M.W., 2011. Sectoral vs. Aggregate Shocks: A Structural Factor Analysis of Industrial Production. Journal of Political Economy 119, 1-38.

Frankel, J.A., and Rose, A.K., 1998. The Endogeneity of the Optimum Currency Area Criteria. The Economic Journal 108, 1009-1025.

Gabaix, X., 2011. The Granular Origins of Aggregate Fluctuations. Econometrica 79, 733–772.

Geweke, J., 1996. Monte Carlo Simulation and Numerical Integration, in: Amman, K.M. and Rust, J. (Eds.), Handbook of Computational Economics, Vol. 1. North-Holland, Amsterdam, pp. 731-800.

Hirata, H., Kose., M.A., and Otrok, C., 2013. Regionalization vs. Globalization. IMF Working Paper, WP/13/19.

Imbs, J., 2004. Trade, Finance, Specialization, and Synchronization. The Review of Economics and Statistics 86, 723-734.

Karadimitropoulou, A., and Leon-Ledesma, M., 2013. World, Country and Sector Factors in International Business Cycles. Journal of Economic Dynamics and Control 37(12), 2913-2927.

Kose, M.A., Otrok, C., and Whiteman, C.H., 2003. International Business Cycles: World, Region, and Country-Specific Factors. American Economic Review 93, 1216-1239.

Kose, M.A., Otrok, C., and Whiteman, C.H., 2008. Understanding the Evolution of World Business Cycles. Journal of International Economics 75, 110-130.

Kose, M.A., Otrok, C., and Prasad, E.S., 2012. Global Business Cycles: Convergence or Decoupling. International Economic Review 53, 511-538.

Long, J.B., and Plosser, C.I., 1983. Real Business Cycles. Journal of Political Economy 91, 39-69.

Norrbin, N.C., and Schlagenhauf, D.E., 1996. The role of International Factors in the Business Cycles: a multi-country study. Journal of International Economics 40, 85-104.

Otrok, C., and Whiteman, C.H., 1998. Bayesian Leading Indicators: Measuring and Predicting Economic Conditions in Iowa. International Economic Review 39, 997-1014.

Timmer, M.P., de Vries, G.J., and de Vries, K., 2015. Patterns of Structural Change in Developing Countries. In J. Weiss, & M. Tribe (Eds.), Routledge Handbook of Industry and Development, 65-83, Routledge.

World Bank, 2016. Global Economic Prospects, January 2016: Who Catches a Cold when Emerging Markets Sneeze?. Washington, DC: World Bank.

Figures

Figure 1: World Factor

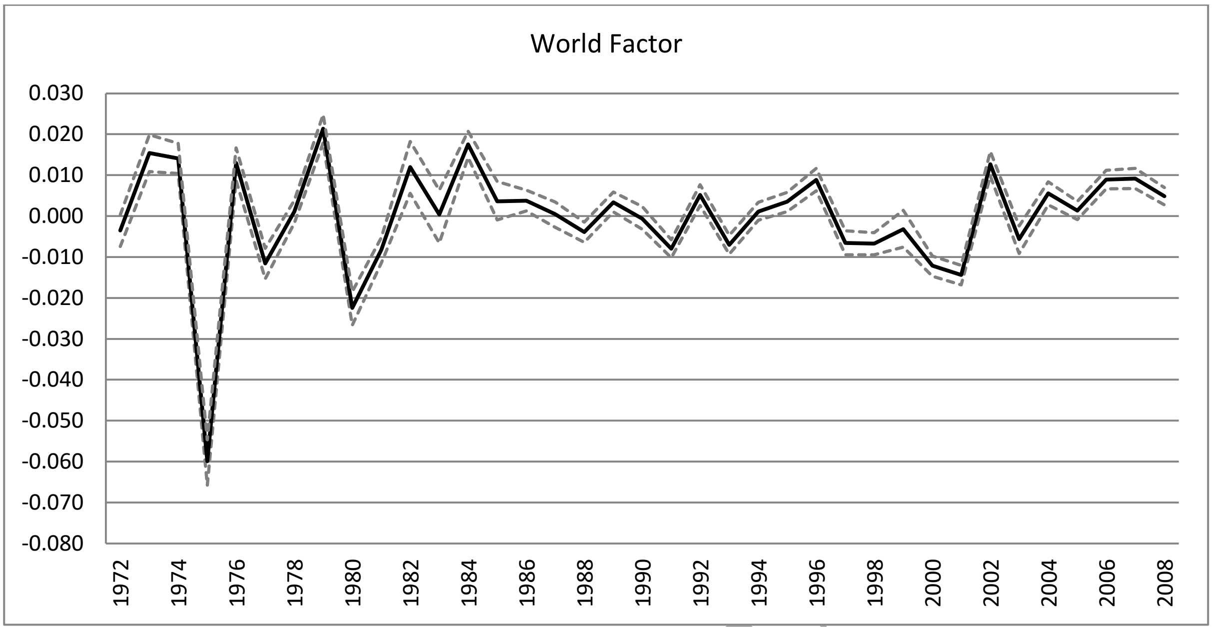


Figure 2: Region Factors

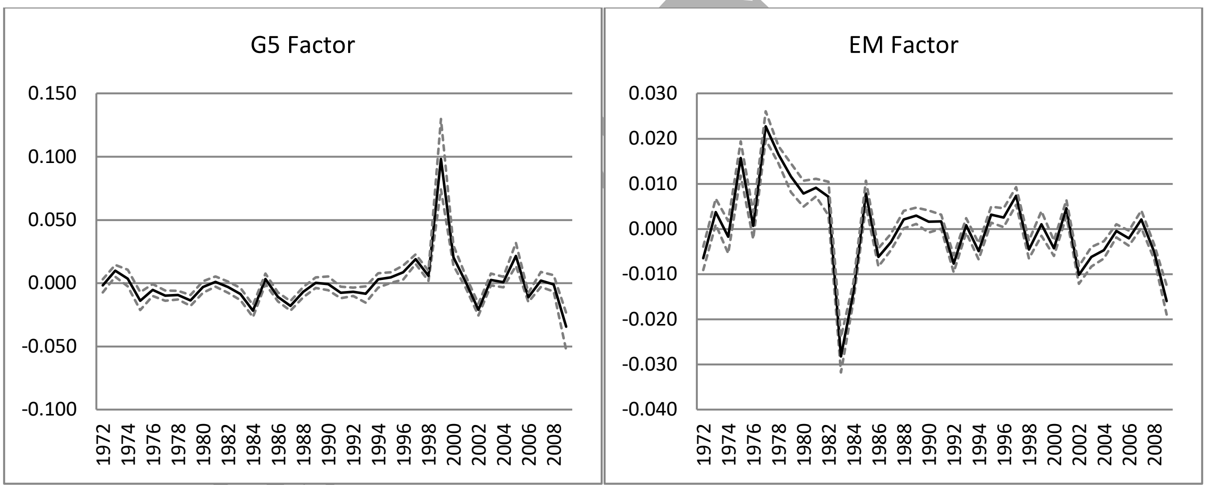
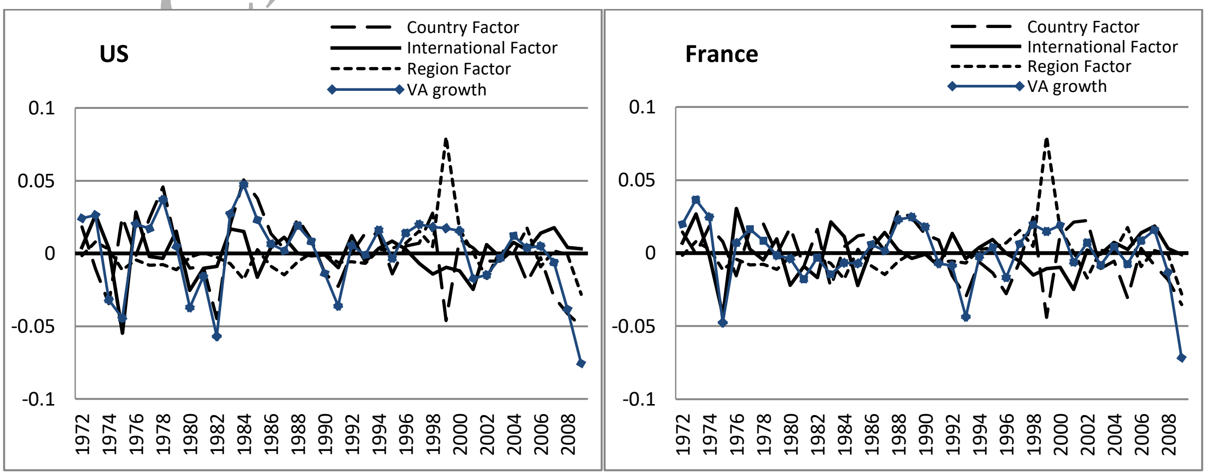


Figure 3: International Factors, Country Factors, and Aggregate VA growth



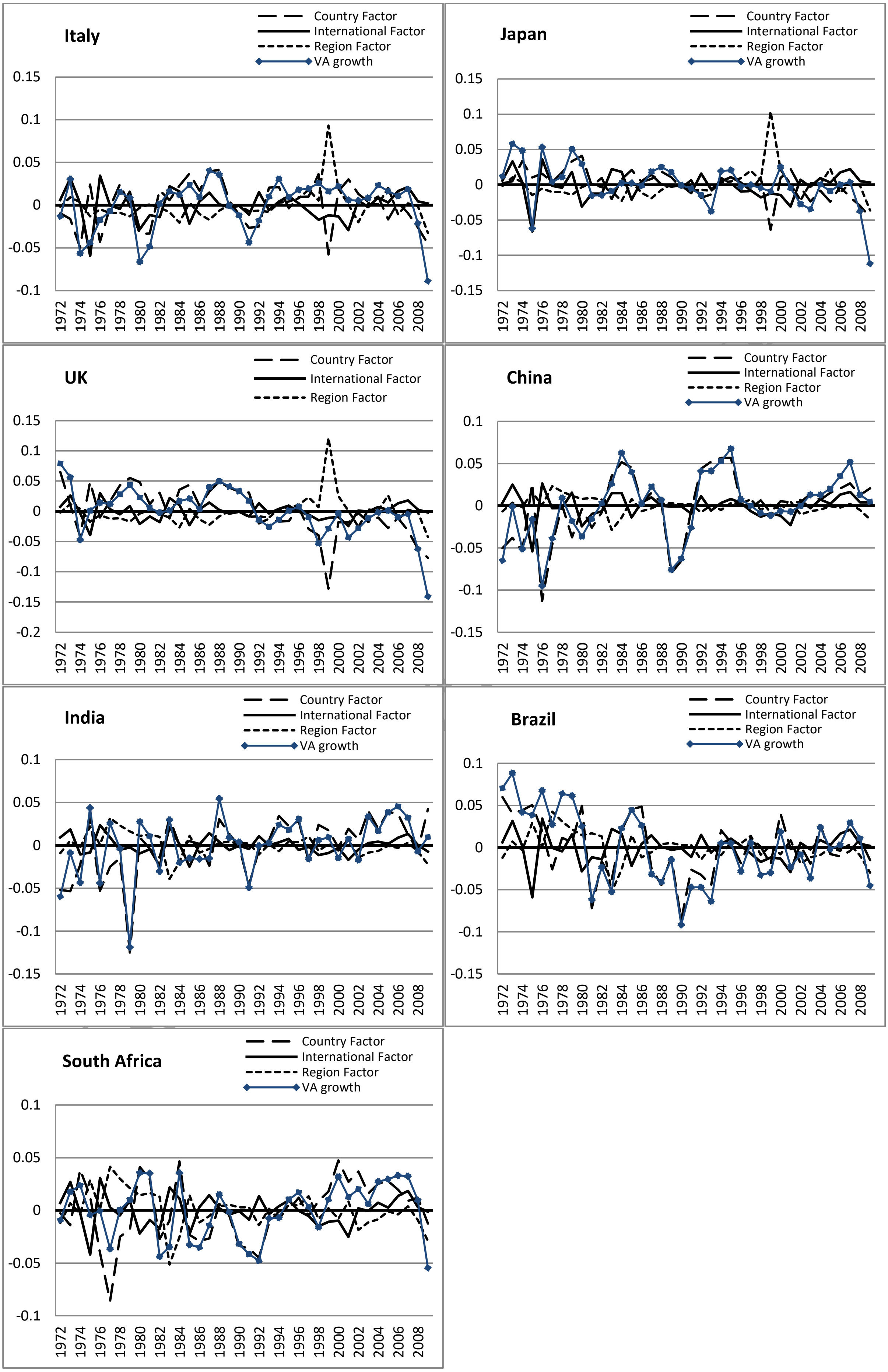

Italy
Japan
UK
China
India
Brazil
South Africa
Country Factor
International Factor
Region Factor
VA growth
1972
1974
1976
1978
1980
1982
1984
1986
1988
1990
1992
1994
1996
1998
2000
2002
2004
2006
2008

Figure 4: Sectoral VA Variance at the country-level due to the World, Sector, Region and Country Factors

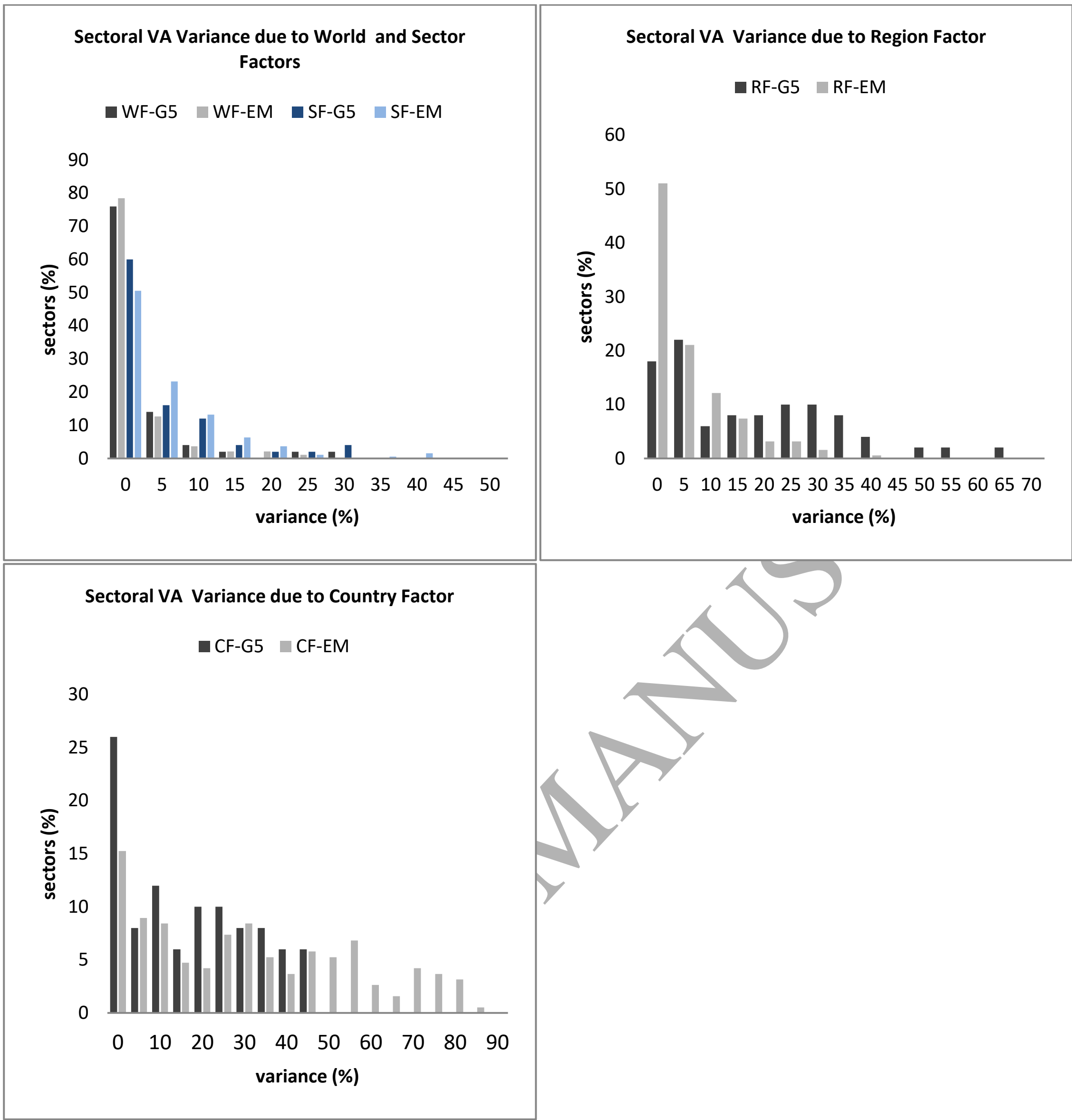
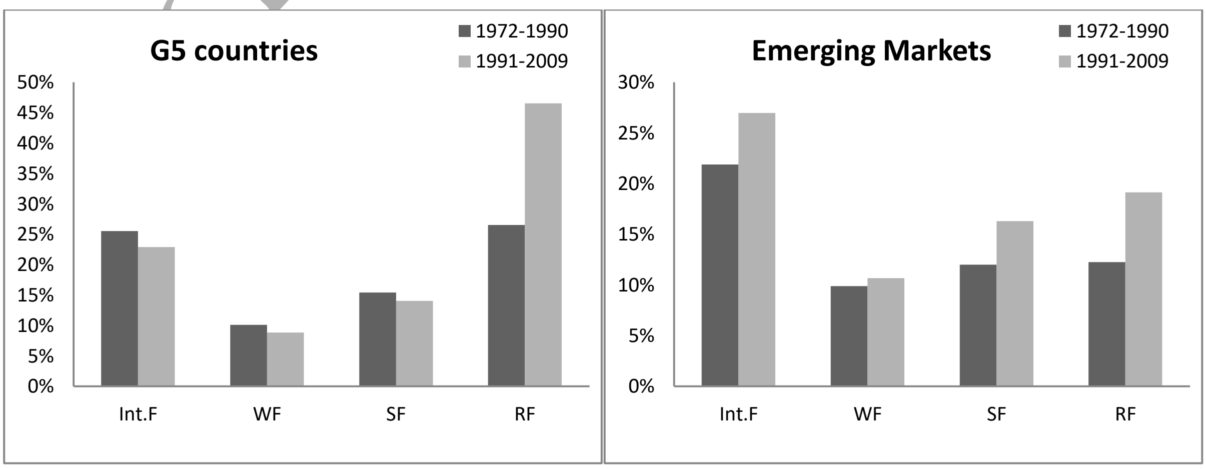
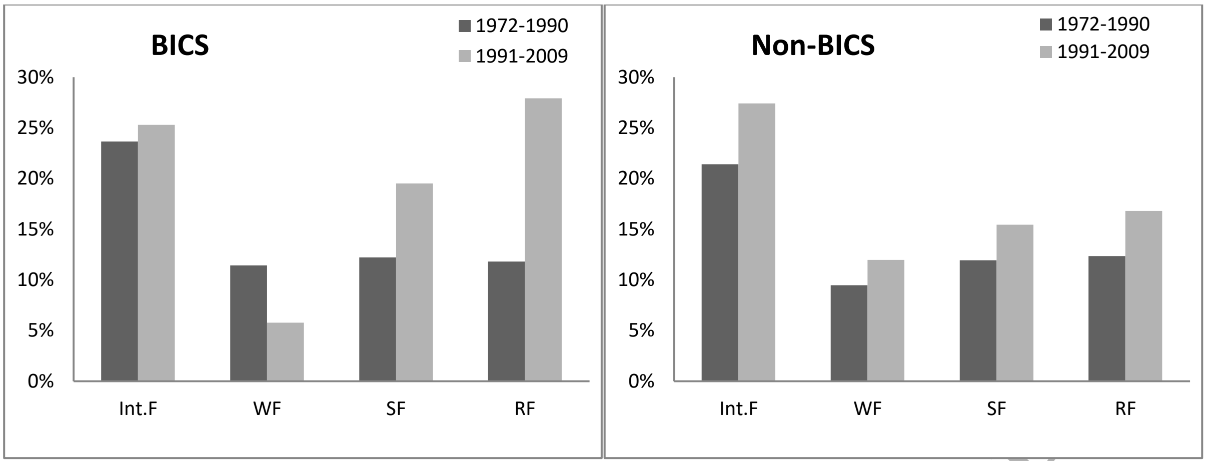


Figure 5: Variance Decomposition for the pre- and post-globalisation period





Note: Int.F is the International Factor (sum of the World and Sector Factors), WF is the World Factor, SF is the Sector Factor, RF is the Region-Specific Factor, and CF is the Country Factor.

Figure 6: Shift-Share Anlysis of Variance Decomposition

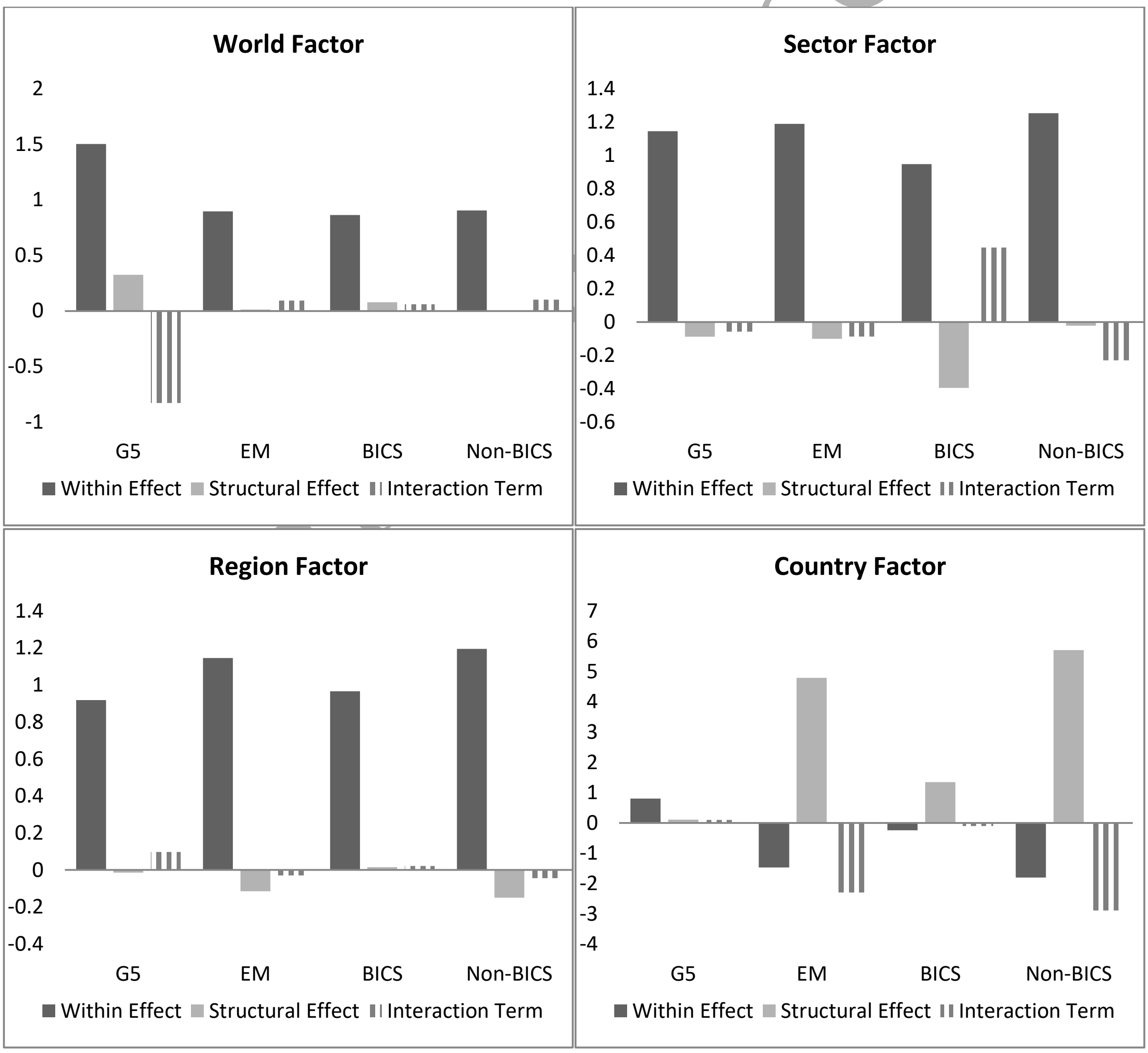


Table 1: Standard Deviation (in %) of the World, Region, Sector and Country Factors

StDev	WF	G5-F	EM-F	CF	SF
1972-1990	1.91	0.81	1.19	2.41	2.02
1991-2010	0.78	2.57	0.56	2.08	1.45

Note: WF is the World Factor, G5-F is the G5 Region-specific Factor, EM-F is the Emerging Markets Region-Specific Factor, SF is the Sector Factor, and CF is the Country Factor.

Table 2: Average correlations between World, Region, Sector, Country Factors and VA growth

	WF	RF	SF	CF
All countries	0.104	0.101	0.157	0.812
G5	0.201	0.208	0.181	0.643
EM	0.078	0.073	0.151	0.856

Note: WF is the world factor, RF is the region factor, SF is the sector factor, and CF is the country factor

Table 3: Variance decomposition (Median, in %) by country

	World	Sector	Region	Country	Idiosyncratic
US	2.21	6.94	25.18	26.91	36.21
France	2.78	7.30	36.26	10.25	39.66
Italy	4.90	10.22	23.51	25.90	33.36
Japan	5.72	16.42	22.21	25.92	26.62
UK	2.67	9.97	16.86	29.75	37.91
Average G5	***3.66***	***10.17***	***24.80***	***23.75***	***34.75***
China	5.90	4.47	3.96	30.59	53.01
India	11.07	6.77	6.25	28.02	44.72
Indonesia	3.93	5.09	6.03	37.78	45.06
Korea	2.18	7.99	6.48	32.37	48.56
Malaysia	5.37	13.71	4.90	23.57	50.11
Philippines	1.57	11.40	17.92	37.91	29.12
Thailand	1.81	18.69	8.89	32.90	35.55
Average Asia	*4.55*	*9.73*	*7.77*	*31.88*	*43.73*
Argentina	1.62	5.56	5.09	59.26	27.14
Brazil	1.83	8.17	9.02	42.43	36.67
Chile	4.42	10.31	7.31	35.67	39.95
Colombia	2.71	7.37	12.97	27.52	47.09
Mexico	1.82	6.49	9.41	49.12	31.57
Peru	0.89	10.36	7.88	56.07	23.22
Average Latin America	*2.21*	*8.04*	*8.61*	*45.01*	*34.27*
Kenya	6.54	8.97	8.46	21.84	50.82
Mauritius	7.76	9.50	3.42	37.72	39.05
Nigeria	8.75	9.11	1.87	11.67	65.51
South Africa	1.52	13.48	14.19	25.78	43.00
Egypt	2.48	2.70	1.98	34.55	56.19
Morocco	5.75	5.35	6.63	24.86	55.19
Average Africa	*5.47*	*8.18*	*6.09*	*26.07*	*51.63*
Average EM	***4.10***	***8.71***	***7.51***	***34.19***	***43.24***

Table 4: Regression of VA variance decomposition on economic structure variables

	World Factor			Sector Factor			Region Factor			Country Factor		
Variable	**Coef**	**t-stat**	**Prob**	**Coef**	**t-stat**	**Prob**	**Coef**	**t-stat**	**Prob**	**Coef**	**t-stat**	**Prob**
PCGDP	0.022	1.41	0.174	0.034	1.07	0.297	0.181	4.77	0.000	-0.247	-4.20	0.020
Trade	0.015	1.07	0.299	0.064	2.71	0.014	-0.015	-0.69	0.496	-0.138	-3.30	0.004
AGR	0.221	3.46	0.003	0.023	0.37	0.713	0.074	1.02	0.321	-1.194	-4.56	0.000
VAVOL	-0.174	-0.38	0.705	-0.459	-1.05	0.308	-2.04	-4.11	0.001	3.972	2.58	0.018
$\boldsymbol{R^2}$	0.36			0.31			0.79			0.67		