Global Business Cycles: Convergence or Decoupling?

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Abstract: This paper analyzes the evolution of the degree of global cyclical interdependence over the period 1960-2005. We categorize the 106 countries in our sample into three groups—industrial countries, emerging markets, and other developing economies. Using a dynamic factor model, we then decompose macroeconomic fluctuations in key macroeconomic aggregates—output, consumption, and investment—into different factors. These are: (i) a global factor, which picks up fluctuations that are common across all variables and countries; (ii) three group-specific factors, which capture fluctuations that are common to all variables and all countries within each group of countries; (iii) country factors, which are common across all aggregates in a given country; and (iv) idiosyncratic factors specific to each time series. Our main result is that, during the period of globalization (1985-2005), there has been some convergence of business cycle fluctuations among the group of industrial economies and among the group of emerging market economies. Surprisingly, there has been a concomitant decline in the relative importance of the global factor. In other words, there is evidence of business cycle convergence *within* each of these two groups of countries but divergence (or decoupling) *between* them.

Keywords: Globalization; Business cycles; Macroeconomic fluctuations; Convergence; Decoupling.

JEL classifications: C11, C32, E32, F42, F41.

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"You either believe in decoupling or globalization-but not both."
Stephen Roach, Financial Times, January 23, 2008

"You can have both decoupling and globalization at the same time."
The Economist, March 8, 2008

I. Introduction

The global economic landscape has shifted dramatically since the mid-1980s. First, there has been a rapid increase in trade and financial linkages across countries. Second, emerging market economies have increasingly become major players and they now account for about a quarter of world output and a major share of global growth. These developments, along with the imminent U.S. recession and concerns about its international spillover effects, have generated a vigorous debate about changes in the patterns of international business cycle comovement. On the one hand, the conventional wisdom suggests that the forces of globalization in recent decades have increased cross-border economic interdependence and led to convergence of business cycle fluctuations. Greater openness to trade and financial flows should make economies more sensitive to external shocks and increase comovement in response to global shocks by widening the channels for these shocks to spill over across countries.

On the other hand, in recent years the impressive growth performance of emerging market economies, especially China and India, seems to have been unaffected by growth slowdowns in a number of industrial countries. This has led to questions about the potency of international channels of business cycle transmission. Some observers have even conjectured that these emerging markets have "decoupled" from industrial economies, in the sense that their business cycle dynamics are no longer tightly linked to industrial country business cycles. These two views of cross-border interdependence have very different implications for the evolution of global business cycles.

What guidance does economic theory offer for discriminating between these two views? Theory delivers rather nuanced predictions about the impact of increased trade and financial linkages on cross-country output comovement. For example, rising financial linkages could result in a higher degree of business cycle comovement via the wealth effects of external shocks. However, they could reduce cross-country output correlations by stimulating specialization of production through the reallocation of capital in a manner consistent with countries' comparative advantage. Trade linkages generate both demand- and supply-side spillovers across countries, which can result in more highly correlated output fluctuations. On the other hand, if stronger trade linkages facilitate increase specialization of production across countries, and if sector-specific shocks are dominant, then the degree of comovement of output could fall (see Baxter and Kouparitsas, 2005).

As for other macroeconomic aggregates, the resource-shifting effect in standard business cycle models implies that global integration should reduce investment correlations by shifting capital to and raising investment growth in countries with relatively high productivity growth. By contrast, rising financial integration should increase consumption correlations by enabling more efficient risk sharing. The empirical validity of these (sometimes conflicting) theoretical predictions remains an open issue.

Our objective in this paper is to provide a comprehensive empirical characterization of global business cycle linkages among a large and diverse group of countries. We focus on the following questions: First, what are the major factors driving business cycles in different groups of countries? Are these factors mainly global or are there distinct factors specific to particular groups? Second, how have these factors evolved as the process of globalization has picked up in pace over the past two decades? The answers to these questions have important implications for the debate on the relative merits of the two competing views about whether global business cycles are converging or decoupling.

We extend the research program on global business cycles in several dimensions. First, our study is much more comprehensive than earlier studies as we use a larger dataset (106 countries) with a longer time span (1960-2005). With few exceptions, the existing literature on international business cycles has focused on industrial countries.[1] Given the rising prominence of the emerging markets in the global economy, and particularly in the context of an analysis of international business cycle spillovers, this narrow focus is no longer tenable. Indeed, the current debate about convergence or decoupling is largely about whether and how emerging markets will be affected by the U.S. business cycle. Our use of a large sample of countries allows us to draw a sharp contrast across the different groups of countries in terms of their exposure to the global

[1] See Kose, Otrok and Whiteman (2008) for a brief survey of the literature studying the extent of business cycles comovement among industrial countries.

economy. In addition, the relatively longer time span of the data enables us to consider distinct sub-periods and, in particular, analyze the changes in business cycles that have taken place during the period of globalization (1985-2005) relative to earlier periods.

Second, unlike most existing studies, we specifically consider the roles played by global cycles and distinguish them from cycles common to specific groups of countries—industrial economies, emerging markets, and other developing economies. This distinction between the latter two groups of non-industrial countries turns out to be important for our analysis.

Third, we study the extent of global business cycle comovement in a number of macroeconomic variables rather than solely focusing on output. A key insight from our brief discussion of theory above is that the common practice of measuring business cycles and spillovers based on fluctuations in output can be rather restrictive. Indeed, our approach of using multiple macroeconomic indicators rather than just GDP to characterize business cycles can be traced back to classical scholars of business cycles (Burns and Mitchell, 1946; Zarnowitz, 1992). The NBER also looks at a variety of indicators for determining turning points in U.S. business cycles.[2]

In addition, we employ a set of recently developed econometric tools to analyze these questions. The novel methodology that we implement is based on estimation of a dynamic factor model and is critical for our purposes. Our model enables us to simultaneously capture contemporaneous spillovers of shocks as well as the dynamic propagation of business cycles in a flexible manner, without a priori restrictions on the directions of spillovers or the structure of the propagation mechanism. We decompose macroeconomic fluctuations in national output, consumption, and investment into the following factors: (i) a global factor, which picks up fluctuations that are common across all variables and countries; (ii) three factors specific to each group of countries, which capture fluctuations that are common to all variables and all countries in a given group; (iii) country factors, which are common across all variables in a given country, and (iv) idiosyncratic factors specific to each time series.

[2] The NBER focuses on the evolution of five indicators—real GDP, real income, employment, industrial production, and wholesale-retail sales. Others have used variables such as real GDP and unemployment to pin down the sources of business cycles (Blanchard and Quah, 1989). King et. al (1991) study joint fluctuations in output, consumption and investment to identify trends and cycles.

The estimated factors reflect elements of commonality of fluctuations in different dimensions of our data. The importance of studying all of these factors in one model is that they obviate problems that could be caused by studying a subset of factors, which could lead to a mischaracterization of commonality. For instance, group-specific factors estimated in a smaller model may simply reflect global factors that are misidentified as being specific to a particular group. Moreover, by including different macroeconomic aggregates, we get better measures of the commonality of fluctuations in overall economic activity. The dynamic factors capture intertemporal cross-correlations among the variables and thereby allow for the effects of propagation and spillovers of shocks to be picked up. This methodology is also useful to analyze how the global and group-specific factors have affected the nature of business cycles within each group of countries over time.

We report a rich set of results about the evolution of global business cycles. Our first major result is that there has been a decline over time in the relative importance of global factors in accounting for business cycle fluctuations in our sample of countries. In other words, there is no evidence of global convergence of business cycles during the recent period of globalization. Even if we use a broader definition of global business cycle convergence by taking the total contribution of all common factors—global and group-specific—there has been little change in overall business cycle synchronicity. This sum has been stable over time because of the substantial increase in the contribution of group-specific factors to business cycles. This brings us to our next interesting result.

During the period of globalization, there has been a modest convergence of business cycles among industrial countries and, separately, among emerging market economies. That is, group-specific factors have become more important than global factors in driving cyclical fluctuations in these two groups of countries. This phenomenon of group-specific business cycle convergence is a robust feature of the data—it is not limited to countries in any particular geographic region and is not a mechanical effect of episodes of crises. The distinction between emerging markets and other developing economies is crucial for uncovering this result. This distinction has become sharper over time as there has been little change in the relative importance of group-specific factors for the latter group, where business cycle fluctuations are largely driven by idiosyncratic factors.

We also find that country-specific factors have become more important for the group of emerging market economies in the recent period of globalization, while they have become less important for industrial economies. The rising comovement among output, consumption and investment in the former group ties in with a recent literature showing that countries with intermediate levels of financial integration—i.e., emerging market economies—have not been able to achieve improved risk sharing during the globalization period (Kose, Prasad and Terrones, 2007). Moreover, the more successful emerging market economies have increasingly depended on domestically-financed investment, rather than relying on foreign capital to boost investment (Gourinchas and Jeanne, 2007; Aizenman, Pinto, and Radziwill, 2007; Prasad, Rajan, and Subramanian, 2007). On the other hand, countries with high levels of financial integration—mostly industrial countries—have been able to use international financial markets to more efficiently share risk and delink consumption and output.

II. Methodology and Data

The econometric methodology that we employ needs to be able to identify different sources of cyclical fluctuations, account for dynamic and persistent relationships among different variables, and be suitable for a large dataset. To meet these requirements, we employ a dynamic latent factor model. We first discuss the main features of our empirical model and then briefly describe the dataset.

II.1 A Dynamic Factor Model

In recent years, dynamic factor models have become a popular econometric tool for quantifying the degree of comovement among macroeconomic time series.[3] The motivation underlying these models is to identify a few common factors that drive fluctuations in large multi-dimensional macroeconomic datasets. These factors can capture common fluctuations across the entire dataset (i.e., the world) or across subsets of the data (e.g., a particular group of countries). The factor structure itself is directly motivated by general equilibrium models as shown in Sargent (1989) and Altug (1989). In our case, we do not interpret the factors as

[3] In addition to analysis of business cycles comovement, factor models have been used in a variety of contexts. See Otrok and Whiteman (1998) for an application to a forecasting exercise, and Bernanke, Boivin and Eliasz (2005) for an application to the analysis of monetary policy.

representing specific types of shocks such as technology—instead, we view them as capturing the effects of many types of common shocks, including technology shocks, monetary policy shocks, etc. Dynamic factor models are particularly useful for characterizing the degree and evolution of synchronization in various dimensions without making strong identifying assumptions to disentangle different types of common shocks.

We construct a model that contains: (i) a global factor common to all variables (and all countries) in the system; (ii) a factor common to each group of countries; (iii) a country factor common to all variables in each country; and (iv) an idiosyncratic component for each series. Since our primary interest is in comovement across all variables in all countries (or groups of countries), we do not include separate factors for each of the macroeconomic aggregates (including factors in yet another dimension would also make the model intractable for the number of countries we study).

The dynamic relationships in the model are captured by modeling each factor and idiosyncratic component as an autoregressive process. Specifically, let $Y_t^{i,j,k}$ denote the growth rate of the i^th^ observable variable in the j^th^ country of economy type k. Here we have three variables per country (indexed by *i*), three economy types (indexed by *k*), and 106 countries (indexed by *j*). The model can then be written as:

$$(1) \qquad Y_t^{i,j,k} = \beta_{global}^{i,j,k} f_t^{global} + \beta_{economy\ k}^{i,j,k} f_t^{economy\ k} + \beta_{\mathrm{country\ j}}^{i,j,k} f_t^{country\ \mathrm{j}} + \varepsilon_t^{i,j,k},$$

$$(2) \qquad \mathrm{f}_t^{\mathrm{m}} = \phi^{\mathrm{m}}(\mathrm{L})\mathrm{f}_{t-1}^{\mathrm{m}} + \mu_t^{\mathrm{m}} \text{ for m} = 1\ldots(1+\mathrm{K}+\mathrm{J}),$$

$$(3) \qquad \varepsilon_t^{\mathrm{i,j,k}} = \phi^{\mathrm{i,j,k}}(\mathrm{L})\varepsilon_{t-1}^{\mathrm{i,j,k}} + \nu_t^{\mathrm{i,j,k}}$$

where $\phi^{i,j,k}(L)$ and $\phi^m(L)$ are lag polynomial operators, $\nu_t^{i,j,k}$ are distributed $N(0,\sigma_{i,j,k}^2)$, μ_t^m are distributed $N(0,\sigma_m^2)$, and the innovation terms μ_t^m and $\nu_t^{i,j,k}$ are mutually orthogonal across all equations and variables in the system. The β parameters are called factor loadings and capture the sensitivity of each observable variable to the latent factors. For each variable, the estimated factor loadings quantify the extent to which that variable moves with the global factor, the factor for its economy type, and the country-specific factor, respectively. The lag polynomials can in principle be of different order; however, for simplicity and parsimony, we restrict them to be AR(3) for each factor and idiosyncratic term. Since we are using annual data, this should capture most spillovers, either contemporaneous or lagged, across variables and countries.

There are two related identification problems in the model given by equations (1)-(3): neither the signs nor the scales of the factors and the factor loadings are separately identified. We identify the signs by requiring one of the factor loadings to be positive for each of the factors. In particular, we impose the conditions that the factor loading for the global factor is positive for U.S. output; that country factors have positive factor loadings for the output of each country; and the factors for each country group have positive loadings for the output of the first country listed in each group in Appendix A.[4] Following Sargent and Sims (1977) and Stock and Watson (1989), we identify the scales by assuming that each σ_m^2 is equal to a constant. The constant is chosen based on the scale of the data so that the innovation variance is equal to the average innovation variance of a set of univariate autoregressions on each time series. The results are not sensitive to this normalization. Technical details about the estimation of the model are in Appendix B.

II.2 Advantages of Dynamic Factor Models

We now briefly review the advantages of our approach, first by contrasting it with some common alternatives. A standard approach to measuring comovement, and one that is widely used in the literature is to calculate sets of bivariate correlations for all variables in a dataset.[5] Deriving summary measures from large datasets requires one to take averages across the estimated correlations, a procedure that can mask the presence of comovement across a subset of the data. One way to reduce the number of bivariate correlations is to specify a country or weighted aggregate to serve as the reference against which other countries' correlations are computed. However, changes in the reference country/aggregate often lead to significantly different results. Such weighting schemes also inevitably give rise to questions about the weights and concerns that a large county may dominate the global business cycle by virtue of its size

[4] The sign restriction is simply a normalization that allows us to interpret the factors in an intuitive way. For example, we normalize the factor loading for GDP growth in the U.S. on the global factor to be positive. This implies that the global factor falls in 1974 and 1981, consistent with the fact that most countries had a recession in those years. If, instead, we were to normalize using Venezuela, an oil exporting country that benefited from the 1974 oil price shock, the factor would rise in 1974. The U.S. factor loading on the global factor would then be negative.

[5] Other measures include: (1) the concordance statistic (Harding and Pagan, 2002), which measures the synchronization of turning points; and (2) coherences (the equivalent of correlations in the frequency domain, although, unlike static correlations, they could allow for lead-lag relationships between two variables). Similar to simple correlations, these other measures are subject to a variety of limitations.

when, in fact, that country may be disengaged from the rest of the world. Moreover, static correlations cannot capture the dynamic properties of the data, such as autocorrelations and cross-autocorrelations across variables.

Factor models obviate these problems. They do not require one to average across variables or define a "numeraire" country. Instead, they identify the common component and, at the same time, detect how each country responds to the common component. For example, suppose one country is positively affected by a shock while a second is negatively affected by the same shock. The factor model will assign a positive factor loading to one country, and a negative one to the other, thereby correctly identifying the sign of the common component for each country. More importantly, factor models are flexible enough that multiple factors can be specified in a parsimonious way to capture the extent of synchronicity across the entire dataset as well as the synchronicity specific to subsets of the data (e.g., particular groups of countries). Furthermore, since the factors are extracted simultaneously, we can assign a degree of relative importance to each type of factor.

In our dynamic latent factor model, country "weights" are derived as part of the estimation process. That is, the econometric procedure searches for the largest common dynamic component across countries (in static factor models, this is labeled the first principal component). For example, if the world contained one large country and a number of small countries, and the small countries moved together but were unrelated to the large country, our procedure would identify that common component across the smaller countries. While some may view this as problematic in that the large country contains a significant part of world GDP, we consider this a virtue, since we are trying to characterize the degree of synchronicity of cycles across a large set of countries. In order to do so, we need to identify which countries in fact move together. Of course, in practice, large countries affect small ones through various linkages and our procedure does capture this.

The factor model is also well suited to studying the joint properties of fluctuations in output, consumption, and investment. Using multiple macroeconomic aggregates, rather than just output, allows us to derive more robust measures of national and global business cycles. Moreover, since each variable can respond with its own magnitude and sign to the common factors, the model can simultaneously capture the effects of changes in comovement across different macroeconomic aggregates. For example, if consumption comovement goes up from one period to the next across two countries, we would observe an increase in the factor loading for consumption in both countries for either the global or group-specific factor (depending on how widespread the increase in consumption comovement is and which groups the two countries belong to). At the same time, we would observe a decrease in the size of the factor loading on the investment variables in those countries. The same would happen, with a greater decline in the factor loading on investment, if the increase in consumption comovement was accompanied by a decrease in investment comovement.

To summarize, our empirical model is quite flexible in capturing the degree of and changes in the patterns of comovement across different countries, groups of countries, and macroeconomic aggregates. It can also handle dynamic propagation of shocks from various sources. The dynamic factor model is in fact a decomposition of the entire joint spectral density matrix of the data. As such, it incorporates all information on the dynamic comovement of the data. In the process, it allows us to identify the relative importance of different types of global, group-specific, country-specific and idiosyncratic factors. The model is computationally intensive but tractable without a priori restrictions on the effects or propagation structure of various shocks.

II.3. Variance Decompositions

We use variance decompositions to measure the relative contributions of the global, group-specific and country-specific factors to business cycle fluctuations in each country. This provides an empirical assessment of how much of a country's business cycle fluctuations are associated with global fluctuations or fluctuations among a group of countries. We estimate the share of the variance of each macroeconomic variable attributable to each of the three factors and the idiosyncratic component. With orthogonal factors, the variance of the growth rate of the observable quantity $Y_t^{i,j,k}$ can be written as follows:[6]

[6] Even though the factors are uncorrelated, samples taken at each pass of the Markov chain will not be, purely because of sampling errors. To ensure adding up, we took a further step for these calculations, and orthogonalized the sampled factors, ordering the global factor first, the regional factor second, and the country factor third. Our simulations suggest that the order of orthogonalization has little impact on the results. In particular, all of the results remain qualitatively similar under alternative orderings, and the quantitative differences are small.

$$\text{var}(Y_t^{i,j,k}) = (\beta_{\text{global}}^{i,j,k})^2 \text{var}(f_t^{\text{global}}) + (\beta_{\text{economy k}}^{i,j,k})^2 \text{var}(f_t^{\text{economy k}}) + (\beta_{\text{country j}}^{i,j,k})^2 \text{var}(f_t^{\text{country j}}) + \text{var}(\varepsilon_t^{i,j,k})$$

Then, the fraction of volatility due to, say, the global factor would be:

$$\frac{(\beta_{\text{global}}^{i,j,k})^2 \text{var}(f_t^{\text{global}})}{\text{var}(Y_t^{i,j,k})}$$

These measures are calculated at each pass of the Markov chain; dispersion in their posterior distributions reflects uncertainty regarding their magnitudes.

II.4 Data

Our dataset, primarily drawn from the World Bank's World Development Indicators, comprises annual data over the period 1960–2005 for 106 countries. Real GDP, real private consumption, and real fixed asset investment constitute the measures of national output, consumption, and investment, respectively. All variables are measured at constant national prices. We compute the growth rates and remove the mean from each series.

We divide the countries into three groups: industrial countries (23 INCs), emerging market economies (24 EMEs), and other developing countries (59 ODCs). Appendix C shows the distribution of countries among the three groups. For our purposes, the key distinction among the EMEs and ODCs is that the former group has attained a much higher level of integration into global trade and finance.[7] For instance, the average growth rate of total trade (exports plus imports) has been more than twice the growth rate of GDP in the former group since the mid-1980s, while the corresponding figure for the ODCs is much lower. EMEs have also received the bulk of private capital inflows going from industrial to non-industrial countries. Over the last two decades, the total gross stocks of foreign assets and liabilities of all EMEs have risen more than five-fold and are now an order of magnitude larger than those of all ODCs.[8]

[7] On average, EMEs also had higher per capita incomes and experienced higher growth rates than ODCs over the last two decades. Over the period 1960-1984, industrial countries on average accounted for more than 70 percent of world GDP (in PPP terms) while the aggregate share of the EMEs was roughly 25 percent. During the globalization period, the share of EMEs in world GDP has increased to 34 percent while that of industrial economies has fallen to 62 percent. The share of ODCs has registered a slight decline over time.

[8] The trade openness ratio for EMEs has risen from 28 percent to 78 percent over the last two decades. Similarly, for INCs, the openness measure has increased from 26 percent to 46 percent during the period of globalization. In contrast, the openness ratio for ODCs has been rather stable around 65 percent. For a detailed account of changes in trade and financial linkages, see Akin and Kose (2008).

To study how business cycles have evolved over time in response to trade and financial integration, we divide our sample into two distinct periods—the pre-globalization period (1960-1984) and the globalization period (1985-2005). There are three reasons for this demarcation. First, global trade and financial flows have increased markedly since the mid-1980s. Countries have intensified their efforts to liberalize external trade and financial account regimes and the fraction of countries with a fully liberalized trade (financial) account in our sample has increased from 20 (30) percent to close to 70 (80) percent over the past two decades.[9] These factors have led to a dramatic increase in global trade flows, both in absolute terms and relative to world income, during the globalization period. For example, the ratio of world trade to world GDP has surged from less than 30 percent in 1984 to more than 50 percent now. The increase in financial flows has also been remarkable as the volume of global assets and liabilities has risen more than ten-fold during the same period (see Lane and Milesi-Ferretti, 2006). In other words, global economic linkages clearly became much stronger during the second period.

Second, after a period of stable growth during the 1960s, the first period witnessed a set of common shocks associated with sharp fluctuations in the price of oil in the 1970s and a set of synchronized contractionary monetary policies in the major industrial economies in the early 1980s. This demarcation is essential for differentiating the impact of these common shocks from that of globalization on the degree of business cycle comovement. Third, the beginning of the globalization period coincides with a structural decline in the volatility of business cycles in both industrial and non-industrial countries.[10]

III. Dynamic Factors and Episodes of Business Cycles

In this section, we examine the evolution of different factors and analyze their ability to track important business cycle episodes since 1960. Since conventional measures of business cycles have tended to focus on fluctuations in output, we restrict our analysis in this section to the decomposition of output growth fluctuations into different factors.

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[9] Moreover, the beginning of the globalization period marks the start of the Uruguay Round negotiations which speeded up the process of unilateral trade liberalizations in many developing countries.

[10] See Blanchard and Simon (2001), McConnell and Perez-Quiros (2000) and Stock and Watson (2005). Explanations for this decline in volatility are many, ranging from “the new economy” driven changes to the more effective use of monetary policy.

III.1. Evolution of the Global and Group-Specific Factors

Figure 1 (top panel) displays the posterior mean of the global factor, along with the 5 and 95 percent posterior quantile bands for the estimated factors. These bands form a 90 percent probability coverage interval for the factor—that is, the probability that the factor lies in this interval is 0.9. The tightness of this interval suggests that the global factor is estimated fairly precisely. The fluctuations in this factor reflect the major economic events of the past four decades: the steady expansionary period of the 1960s; the boom of the early 1970s; the deep recession of the mid-1970s associated with the first oil price shock; the recession of the early 1980s stemming from a variety of forces including the debt crisis and the tight monetary policies of major industrialized nations; the mild recession of the early 1990s; the 2001 recession and the subsequent recovery.

The behavior of the global factor is also consistent with several interesting stylized facts pertaining to the amplitude and sources of global business cycles. First, the global factor has become less volatile after the mid-1980s. In particular, our estimations suggest that the standard deviation of the global factor decreased from 1.4 percent in the 1960-1984 period to 0.5 percent during 1985-2005. This is consistent with the structural decline in the volatility of business cycles in a number of countries we discussed earlier.

Second, consistent with other studies, fluctuations in the price of oil appear to be related to the turning points of global business cycles (see Backus and Crucini, 2000). For example, the largest troughs in the global factor closely coincide with the sharp increases in the price of oil, as the major oil price increases of 1974 and 1980-81 were associated with global recessions. However, the contemporaneous correlation between the global factor and the growth rate of the oil price is rather small, suggesting that there are other important factors besides oil prices that matter for global business cycles.[11] Third, the worldwide recession in the early 1980s was deeper than the one in the mid-1970s.

The group-specific factors are by assumption orthogonal to the global factor and, as we noted earlier, any common shocks affecting all countries will be picked up by the global factor. The group-specific factors, however, capture any remaining comovement among countries

[11] The correlation between the global factor and the world price of oil, measured by the index of average spot prices (from the IMF's International Financial Statistics), is -0.04.

within each group (Figure 1, lower panels).[12] The cross-group correlations among these factors are around 0.56. One interpretation of these results is that, once we account for the global cycle, there are still distinct group-specific cycles that appear be highly correlated across groups.[13] The group-specific factors tend to be more volatile than the global factor, which is not a surprise. The fluctuations in the group-specific factors also reflect some important cyclical episodes. For example, the INC group-specific factor captures the 2001 recession and subsequent recovery.

III.2. Country Factors and Domestic Economic Activity

We now examine the evolutions of the global, group-specific, and country factors for a few selected countries and see how those factors match up with actual output growth in those countries. To make the scales of the factors and output growth comparable for each country, the factors are multiplied by their respective factor loadings. This implies that the sum of the three scaled factors and the idiosyncratic component is equal to the growth rate of output of each country. The results are presented in Figure 2.

The top left panel shows the median of the estimated U.S. country-specific factor along with the global factor, the industrial country group-specific factor, and the growth rate of U.S. output. The U.S. country factor captures most of the peaks and troughs of the NBER reference dates for U.S. business cycles.[14] While the U.S. country factor and the global factor exhibit some common movements, there are some notable differences between the two factors in almost every decade. Despite these differences, the contemporaneous correlation between the fluctuations in the U.S. output and the global factor is strongly positive (0.44).

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[12] In small samples, it is possible that the global and group-specific factors will be correlated due to a spurious correlation associated with the short sample. In all the results reported here, we impose orthogonality by regressing the group-specific factors on the global factor and retaining the residual. The correlation between the industrial country factor and EMEs (ODCs) factor in our sample is around 0.6 (0.5). The average correlation between the global factor and group-specific factors is less than 0.1. We calculated 5 percent and 95 percent quantile bands for all of the estimated factors, but leave them out of the plots to reduce clutter. Plots showing the quantile bands are available from the authors.

[13] Another possibility is that there is a second global factor that we have not accounted for. We checked whether this is the case by conducting additional simulations but the results suggest this is not the case.

[14] The NBER reference business cycle dates for the U.S. are as follows: Troughs: Feb. 1961, November 1970, March 1975, July 1980, November 1982, March 1991, and November 2001. Peaks: April 1960, December 1969, November 1973, January 1980, July 1981, July 1990, and March 2001. All other reference business cycle dates are taken from IMF (2002).

The top right panel of Figure 2 displays the global factor, the industrial country group-specific factor, the country-specific factor and the actual output growth rate for Japan. The rapid growth rate of the Japanese economy during the 1960s was captured by the country factor while the impact of the global factor during this period was rather minor. Nevertheless, there is a relatively high correlation between the global factor and the Japanese country factor (0.53) from 1960 to 1992. Since the early 1990s, however, this link appears to have disappeared as the country-specific factor plays a more significant role in driving business cycles in Japan and the correlation drops to -0.23 during the period 1993-2005.

The lower panels of Figure 2, which plot the estimated factors for Mexico and Singapore, illustrate that the country-specific factors play a relatively more important role in explaining business cycles in the EMEs. These factors also exhibit some important historical business cycle episodes. For instance, the Mexican country factor captures the Tequila crisis of the 1994-95.

IV. Sources of Business Cycle Fluctuations: 1960-2005

We now examine the sources of business cycle fluctuations with the help of variance decompositions over the full sample period. As a summary measure of the importance of the factors, we present the average variance shares (within the relevant groups of countries) attributable to each factor for the world and the three groups of countries defined earlier. We do not report standard errors for these cross-country averages but will do so when we look at individual country results. Although most of the literature on international business cycle transmission has tended to focus on output as the key indicator of domestic cycles, we discuss the sources of fluctuations in consumption and investment as well. [15]

IV.1 Common Cycles: Global and Country-Specific Factors

Table 1 shows that the global factor accounts for a significant fraction of business cycle fluctuations in all three macroeconomic variables over the period 1960-2005, implying that there is a "world business cycle." The global factor on average explains 11 percent of output growth variation among all countries in the sample. It also accounts for 9 percent and 6 percent of the

[15] We also calculated the median (rather than mean) variance shares attributable to each factor for the full sample and each group of countries. These were generally close to the average shares reported in Tables 1-6, indicating that there are no obvious outlier countries driving our results. Hence, we only report results using means. The results using medians are available from the authors.

volatility of growth rates of consumption and investment, respectively. While these numbers may seem small at first glance, note that the common factor across the three macroeconomic aggregates is for a very large and diverse set of countries.

The factor loadings associated with output and consumption growth on the global factor are positive for most countries (i.e., the posterior distributions of the factor loadings have very little mass in symmetric intervals about zero).[16] Since the global factor is identified by a positive factor loading for U.S. output growth, these findings also imply that positive developments in the U.S. economy are generally associated with positive developments in the rest of the world.

While the global factor is important in each group of countries, on average it plays a more dominant role in explaining business cycles in industrial countries. The average variance share of output growth attributable to the global factor in industrial countries is 27 percent, about three to four times as much as in the two groups of nonindustrial countries. The global factor is also associated with a substantial share of the variance in consumption and investment growth among industrial countries, accounting on average for 24 percent and 12 percent of the total variance of these variables, respectively. These shares are also much larger than the corresponding shares for EMEs or ODCs.

Once we account for the world business cycle, are there common cycles across any of the remaining groups of countries? Table 1 shows that the group-specific factor accounts for about 5 percent of output growth fluctuations in the full sample. This factor, like the global factor, is also more important for industrial countries than for EMEs or ODCs. On average, it accounts for 13 percent of output growth fluctuations in industrial countries, compared to 6 percent and 2 percent, respectively, for EMEs and ODCs.

A more comprehensive measure of how much a country's cyclical fluctuations are tied in to those of other countries is to look at the sum of the variance contributions of the global and group-specific factors. The rankings of the different groups remain much the same, although the magnitudes are of course larger. Among industrial countries, the total contribution of these two factors averages 41 percent for output and nearly 30 percent for consumption and investment. For EMEs, the corresponding averages are 14 percent and 9 percent, respectively. The histogram in Figure 3 shows the cross-country distribution of the variance contributions of the common factors. It confirms that a significant fraction of output variation is indeed attributable to the

[16] We do not report the factor loadings; they are available from us upon request.

common factors. In half of the countries in our sample, the common factors together account for more than 10 percent of the variation in output growth.

IV.2 National Cycles: Country and Idiosyncratic Factors

The country and idiosyncratic factors play important roles in driving business cycles around the world (Table 1). The country factor is on average more important in explaining output variation than is the idiosyncratic factor (47 percent versus 35 percent), but the reverse is true for fluctuations in consumption and investment. Looking across the three groups of countries, it is evident that as countries become more developed (and, as an empirical corollary to development, also become more exposed to global trade and financial flows), the global and group-specific factors appear to become more relevant in explaining national business cycles at the expense of the country and idiosyncratic factors.

A striking result is that, among EMEs, country-specific factors account for 60 percent of the variation in output, much higher than in industrial countries (39 percent) or ODCs (44 percent). This means that the degree of comovement across the three main macroeconomic aggregates is much greater within countries in this group, once we've stripped out the part of the comovement attributable to factors that are common across all countries in the sample or across all EMEs. Interestingly, the pattern is reversed for consumption fluctuations in EMEs. Among these countries, the contribution of the idiosyncratic factor is highest (51 percent) and the combined share of the global and group-specific factors in explaining consumption fluctuations is only 8 percent. This pattern holds for ODCs as well, with the total contribution of common factors to consumption fluctuations amounting to only 5 percent. Taken together, these results tie in well with a recent literature showing that developing countries have not been able to achieve much international risk sharing, as measured by correlations of domestic consumption with world consumption (or income). Their consumption fluctuations are closely correlated with their own output fluctuations and, in addition, their consumption fluctuations are not correlated with those of other countries. We will discuss this result in greater detail in later sections when we explore the evolution of global business cycles.

We also note that, for the sample as a whole and also for each group of countries, the total contribution of the global and group-specific factors is greater for output than for consumption. Indeed, Figure 4 shows that this is true even when we look at the global and group-specific factors by themselves. This implies that, on average, country-specific and idiosyncratic factors play a more important role in explaining consumption fluctuations than is the case for output fluctuations. This result echoes a well-known stylized fact in the literature that, contrary to the predictions of conventional theoretical models of international business cycles, output is more highly correlated across countries than consumption (Backus, Kehoe, and Kydland, 1995, refer to this as the "quantity anomaly").

Another notable result from Table 1 is that, among ODCs, the contribution of the idiosyncratic factor is greater than that of any other factor. This is true for all variables, but especially so for investment, where on average the idiosyncratic factor accounts for 73 percent of fluctuations. This finding suggests that investment fluctuations in these countries do not seem to be closely tied to either domestic or world business cycles.

Although the results in Table 1 reveal interesting contrasts across different groups of countries, they also mask large differences in the relative importance of different factors among individual countries. This becomes evident even when we use a finer breakdown of the three coarse country groups. Table 2 is a counterpart of Table 1 but shows the results for smaller groups of industrial countries. These results are based on the estimation of the full model and the group-specific factor here refers to that for all industrial countries. On average, the global factor is more important for the G-7 and EU-12 countries than for other groups. The U.S. and Canada, in particular, seem to march to their own beat compared to other groups of industrial countries. The differences are even more stark when we look at the results for individual countries.[17]

IV.3. Summary

To summarize, there are three major results from our analysis of variance decompositions for the period 1960-2005. First, there exists a global business cycle. The global factor accounts for a modest but significant share of macroeconomic fluctuations across all country groups, although it is more important for explaining business cycles in industrial countries than in EMEs or ODCs. Second, there appear to be cycles specific to each group of countries, but even the group-specific factor plays a significantly more important role among industrial countries than among the other two groups. This is consistent with other evidence that industrial country

[17] Detailed variance decompositions for each country in our sample are available from the authors upon request.

business cycles are more closely aligned with each other and with the global business cycle. As noted earlier, we do not weight countries by their GDP weights, so this is not a mechanical result. Third, the contributions of global and group-specific factors together to the variance of output growth are much higher—across country groups, time periods etc.—than their contributions to the variance of consumption growth, suggesting that there are still unexploited opportunities for international risk sharing. This differential is greater for EMEs and ODCs than for industrial countries, implying that the potential benefits of efficient international risk sharing could be even greater for these two groups (see Prasad et. al, 2003).

V. Globalization and the Evolution of International Business Cycles

In light of our earlier discussion of the effects of global trade and financial integration, a logical (and intrinsically interesting) question is whether—and, if so, how—the patterns of international business cycle synchronicity have changed over time in response to the forces of globalization. In this section, we first provide an analysis of this question. Next, we consider the evolution of the extent of risk sharing around the world based on cross-country comovement of consumption. We then briefly analyze how the contributions of different factors to investment fluctuations have evolved over time.

V.1 Convergence or Decoupling?

The convergence hypothesis suggests that, with closer economic integration, business cycles should become more synchronized across countries over time. Table 3 shows the variance decompositions in a manner analogous to Table 1 but based on models estimated separately for the pre-globalization (1960-84) and globalization (1985-2005) periods.[18] Contrary to the convergence hypothesis, the average contribution of the global factor to output fluctuations *falls* in half, from 15 percent to 7 percent for the full sample. The same pattern holds for consumption

[18] By estimating the model over two sub-samples we are allowing the model parameters, such as the factor loadings and those that determine the structure of propagation of shocks, to vary across sub-samples. This will yield a different variance decomposition. However, the estimate of the factor itself is very similar whether estimated over the full sample or over subsamples. This result is not very surprising as the index of common activity in a period should not be affected by data many periods away. It is also consistent with the recent work of Stock and Watson (2007) who show that latent factors can be estimated consistently despite parametric instability.

fluctuations and, to a much lesser degree, for fluctuations in investment (see Figure 5). These patterns also hold up for each of the country groups. In fact, they are much stronger when we look at output fluctuations by country group. For industrial countries, the average contribution of the global factor falls dramatically, from 28 percent to 9 percent. The decline is also large for EMEs—from 13 percent to 4 percent—while it is somewhat smaller for ODCs—from 10 percent to 7 percent.

In contrast to the declining importance of the global factor, the group-specific factor has on average played an increasingly more dominant role in explaining business cycles over time (Figure 6). For example, the average share of the variance of output and consumption attributed to the group-specific factor has nearly doubled during the globalization period. These patterns are particularly strong, for all three macro aggregates, among the industrial countries and EMEs. In contrast, the group-specific factor for ODCs has played only a minor role in either period. Our long sample, which covers a substantial period of the recent era of globalization, and our demarcation of the pre-globalization and globalization periods are essential in enabling us to identify the emergence of group-specific cycles in the industrial countries and EMEs during the period of globalization. In the next section, we also study the significance of the temporal changes in the importance of global and group-specific factors at the country level and show that these changes are indeed statistically significant.

As we discussed earlier in the paper, a useful metric to measure the extent of business cycle synchronization around the world is the sum of the variance shares of the global and group-specific factors. Interestingly, when we look at the total contributions of these two common factors, there is much greater stability in their contributions to fluctuations in each of the macro aggregates and for each of the country groups (Table 3 and Figure 7). This is of course the consequence of a substantial increase in the relative importance of the group-specific factor. For instance, looking at the variance decompositions for output fluctuations, the relative contributions of the group-specific factor rise from 17 percent to 31 percent for industrial countries and from 3 percent to 9 percent for EMEs. This largely offsets the decline in the variance contributions of the global factor, implying that the sum of the contributions of the two factors is only slightly smaller in the globalization period relative to the pre-globalization period. These results also show that, contrary to the convergence hypothesis, national business cycles have not in general become more synchronized at the global level.

Our findings suggest the need for a nuanced approach to the hypotheses of convergence and decoupling. While there appears to be no support for the hypothesis of global convergence of business cycles, there is a higher degree of synchronization in business cycles within the groups of industrial countries and EMEs during the globalization period, implying that the convergence hypothesis is valid at least for these groups of countries. At the same time, the emergence of group-specific cycles provides partial support for the decoupling hypothesis as it suggests that business cycles in EMEs are now influenced more by their own group-specific dynamics than they were in the pre-globalization period.

How can we explain these results? As noted earlier, there were large common disturbances during the pre-globalization period—the two oil prices shocks—and some correlated shocks in the major industrial countries, notably the disinflationary monetary policy stance in the early 1980s and the associated increase in real interest rates in the group of industrial countries.[19] From the mid-1980s onward (globalization period), however, common global disturbances have become less important in explaining international business cycle fluctuations. These developments have led to a decline in the importance of global factor in explaining business cycles.

At the same time, intra-group trade and financial linkages among industrial countries and EMEs have risen rapidly, especially after the mid-1980s. While there has been a sharp increase in intra-group financial linkages among industrial countries, intra-group trade linkages have become particularly strong among EMEs during this period. For example, the share of intra-group trade in the total international trade of EMEs doubled from less than 18 percent in 1984 to 36 percent in 2005. During this period, EMEs' trade with the group of industrial countries as a share of the EMEs' total trade has declined from 70 percent to 50 percent. Moreover, during the period of globalization, the countries in these two groups have increased the pace of diversification of their industrial (and trade) bases. This has been accompanied by a greater degree of sectoral similarity across countries within each group (see Akin and Kose, 2008). With these changes, intra-group spillovers have begun to contribute more to concurrent cyclical fluctuations than common disturbances. These changes have been associated with a notable increase in the roles played by group-specific factors for the groups where such intra-group

[19] Recent research shows that the implementation of similar macroeconomic policies can lead to a higher degree of business cycle synchronization (see Darvas, Rose, and Szapáry, 2005).

linkages have become much stronger. Not surprisingly, the importance of the global and group-specific factors in explaining business cycles in ODCs, the group least exposed to the forces of globalization, has barely changed between the two periods.

How do our findings compare with the results in the earlier literature? Earlier studies have typically focused on just output fluctuations and limited their analysis to groupings of countries within the same geographic region. However, these studies often report conflicting results. For example, some recent papers document that there is a distinct European business cycle while others argue the opposite.[20] Other authors find regional cycles specific to East Asia and North America (see Helbling et. al, 2007). Kose, Otrok, and Whiteman (2008) find that a common G-7 factor, on average, explains a larger share of business cycle variation in the G-7 countries since the mid-1980s compared with 1960–72. [21] This finding is consistent with our results since we also report that the group-specific factor has become more important in accounting for business cycles in industrial countries since the mid-1980s. As we discuss in the next section, the increase in the share of variance due to the group-specific factor is quite large for the G-7 countries.

Rather than focusing on specific regions or groups of countries, our analysis provides a global perspective about the evolution of business cycles. First, the statistical model we employ simultaneously estimates a global factor and factors specific to particular groups of countries. This avoids the problem that, while countries in groups (regional or otherwise) could display comovement, the source of this comovement may not be distinctly group-specific, but rather, worldwide. Our analysis also shows that the relevant grouping for detecting common cycles is based not necessarily on geographic proximity but on levels of economic development and

[20] For evidence of a European business cycle, see Artis, Krolzig, and Toro (2004) and references therein. But Canova, Ciccarelli, and Ortega (2007) argue that, since the 1990s, the empirical evidence does not reveal a specific European cycle. Bordo and Helbling (2004) find a trend toward increased synchronization among industrial countries, while Monfort et. al (2003) conclude that the degree of comovement among G-7 economies has been declining. Changes in bilateral output correlations often are not significant, a point emphasized by Doyle and Faust (2005).

[21] They document that business cycle synchronization among the G-7 countries increased during the 1970s and early to mid-1980s. The subsequent decline reflects decreased synchronization with Japan and, to a lesser extent, Germany. Stock and Watson (2005) report that the share of output fluctuations in the other five G-7 countries that can be attributed to common factors increased from 1960-83 to 1984-2002.

integration into global trade and financial markets. Moreover, our sample is much more comprehensive than those used in earlier studies.[22]

Do stronger global linkages result in an increase in the degree of international business cycle comovement as suggested by our findings? A number of studies report that cross-sectional differences in bilateral output correlations are systematically related to differences in the strength of bilateral trade and financial linkages. In addition, financial linkages are an important factor in explaining higher degrees of synchronization of both output and consumption fluctuations.[23] While the latter is to be expected, as financial integration should reduce country-specific income risk through asset diversification, the former is less obvious since increases in financial integration between two countries could, in principle, reduce the correlation between their outputs because of increased specialization (see, for instance, Kalemli-Ozcan, Sorensen, and Yosha, 2003).

V.2 Consumption Comovement

We turn next to look at the evolution of variance shares in explaining consumption fluctuations. For industrial countries, the increase in the variance contribution of group-specific factors to consumption fluctuations is particularly large—from 9 percent to 24 percent (Table 3)—but the joint share of the global and group-specific factors is unchanged. For EMEs and ODCs, the two common factors jointly account for a slightly *lower* share of consumption fluctuations in the globalization period. One interpretation of these results is that industrial countries have been able to use financial globalization to effectively share risk amongst themselves, a result found by various other authors as well (Sorensen, Wu, and Zhu, 2007). On the other hand, EMEs and ODCs are yet to attain this benefit of globalization as their consumption fluctuations are still closely tied to domestic cycles (see Kose, Prasad and Terrones, 2007). Consumption comovement measured in this manner is of course not a decisive test of risk sharing, although a broad class of open economy models does yield this interpretation.

[22] For instance, Kose, Otrok and Whiteman (2003) use data from 60 countries, but their sample period is limited to1960-1990. The use of recent data is important since globalization really picked up steam only in the mid-1980s. Moreover, our use of a larger sample (and larger sub-samples within each group) allows us to draw a sharper contrast across country groups in terms of their exposure to the global economy.

[23] For the impact of trade linkages, see Baxter and Kouparitsas (2005) and the references therein. For financial linkages, see Imbs (2006) and Kose, Prasad, and Terrones (2003).

V.3. Dynamics of Investment

For industrial countries and EMEs, the share of investment variance attributable to the global and group-specific factors goes up in the globalization period. This is a curious result for which conventional theoretical models do not yield a convincing explanation. While one can easily rationalize the increase in the importance of the global and group-specific factors in explaining output and consumption variation over time, it is not clear what drives the increase in the investment variance explained by these common factors. In standard stochastic dynamic business cycle models, stronger trade and financial linkages generally lead to lower investment correlations across countries. Reduced restrictions on capital and current account transactions should induce more "resource shifting", through which capital and other resources rapidly move to countries with more favorable technology shocks (see Backus, Kehoe, and Kydland, 1995; and Heathcote and Perri, 2002).[24]

V.4. Summary

We now summarize our key results from this section. The global factor has become less important for macroeconomic fluctuations in industrial economies and EMEs during the period of globalization. In addition, there has been a slight decrease in the degree of international synchronization of business cycles as measured by the joint contribution of the global and group-specific factors to explaining business cycles in the globalization period. By contrast, for both industrial countries and EMEs, the importance of group-specific factors has increased markedly. This result runs contrary to the notion that globalization induces greater business cycle synchronicity across all countries, rather than just groups of countries at comparable stages of economic development. These patterns hold up not just for output, but also for consumption and investment fluctuations. In short, there has been a substantial convergence of business cycles among industrial economies and among EMEs, but there has also been a concomitant divergence or decoupling of business cycles *between* these two groups of countries.

Our results point to two dimensions in which the data do not support the predictions of conventional theoretical models. Globalization has not yet been associated with an increase in

[24] Some recent theoretical papers produce results consistent with the dynamics of investment we report here In Head's (2002) model, cross-country correlations of investment are positive because of increasing returns to the worldwide variety of intermediate goods. Also see Heathcote and Perri (2004).

the degree of risk sharing achieved by EMEs and ODCs as would be expected on the basis of standard international business cycle models. Moreover, contrary to the predictions of such models, the importance of global and group-specific factors for investment fluctuations has risen during the period of globalization, implying a higher degree of cross-country comovement of fluctuations in this variable.

VI. Sensitivity Experiments

We now examine our key results through different lenses in order to verify their robustness and understand their implications.

VI.1. Results for Sub-groups of Countries

First, we look at smaller groups of countries to check if a particular set of them may be driving the results. For instance, there has been a sharp increase in trade and financial flows amongst EU countries, especially since the time when the EMU started looking like a reality. Among the EMEs, the level of trade and financial integration among Asian economies has increased quite sharply over the last decade. Perhaps the result we have uncovered is specific to such smaller groups of countries.

Table 4 shows cross-country means from the decompositions for selected sub-groups within the larger group of industrial countries. As before, the decompositions are based on estimates of the full model and the group-specific factor refers to the factor common across all industrial countries. The top panel replicates the relevant panel from Table 3 as a benchmark. The key patterns we identified for industrial countries—in particular, an increase in the contribution of the group-specific factor, a decline in the contribution of the global factor, and a small decline in the sum of the two--come through very strongly for the G-7 and the EU-12. The patterns are similar, although less strong, when we consider just the U.S. and Canada by themselves.

Table 5 shows the results of a similar exercise for EMEs, using regional groupings of countries. Our main result comes through very strongly for emerging markets in both Asia and Latin America, indicating that our key result is not an Asia-centric phenomenon. For instance, among the emerging markets in Latin America, the contribution of the global factor to the variance in output growth fluctuations falls from 23 percent in the pre-globalization period to 5 percent in the globalization period. The contribution of the group-specific factor, by contrast, goes from 1 percent to 10 percent. The results for Africa are mixed and do not show any clear patterns.

Table 6 has results for regional groupings among the ODCs. One interesting pattern is that the total contribution of the world and group-specific factors is on average much smaller for Asian and African ODCs than it is for Latin American ones during the pre-globalization period. For the Latin American countries, the contribution of the global factor declines in the globalization period but the contribution of the group-specific factor is small in both periods, implying that common factors have a far less important role in macro fluctuations in these countries during the globalization period.

VI.2. Changes in the Importance of Global and Group Factors: Country-Specific Results

The next question is whether the averages that we have presented in the tables so far are representative of what is going on at the country level. To address this issue, for each country we now break down the relative contributions of the different factors to each of the variables. Figures 8-9 show the relative contributions of the global and group-specific factors to output fluctuations in individual industrial countries and emerging markets, with the contributions shown separately for the pre-globalization and globalization periods. We also show the posterior coverage intervals (of length two standard deviations) around the posterior means of the estimated variance contributions. Non-overlapping posterior coverage intervals indicate statistically significant changes between the two periods.

Among industrial countries, the variance contribution of the global factor drops from the first period to the second for 16 countries, remains unchanged for 6 others, and increases for only one country. The picture is reversed for the relative importance of the group-specific factor, which goes up for 13 countries and declines for 2. These patterns are quite similar when we look at emerging markets as well, with the relative importance of the global factor going up for only 2 countries but declining for 12. The relative importance of the group-specific factor, by contrast, rises for 14 emerging markets and declines for none of them.

Thus, the individual country results confirm that the relative contribution of the global factor to industrial country and emerging market business cycles has fallen significantly in the globalization period, while the contribution of the respective group-specific factors has risen.

VI.3. Implications of Crises

Another important question is whether our results are driven entirely by crises. This is a concern mainly for emerging markets, some of which experienced simultaneous crises. During the globalization period, the most prominent widespread crisis has of course been the Asian financial crisis of 1997-98, which directly affected a handful of countries in our sample. We cannot just exclude the crisis years since they are an integral part of the analysis of fluctuations; from a more mechanical perspective, that would also distort the lag-lead patterns in the data. Nevertheless, to account for this episode, we first re-estimated the models including dummies for the crisis years (the models already include country fixed effects) and interactions of those dummies with the countries that were hardest hit by the Asian crisis (Korea, Malaysia, Philippines, Thailand). Second, we used the original model estimates and then calculated the mean pre-globalization and post-globalization contributions of different factors for the emerging markets group excluding the crisis countries. Neither of these experiments yielded results very different from the ones that we have reported so far (results are available from the authors).

VI.3. Alternative Breakpoints

Another issue relates to the choice of breakpoint. In Section II, we have already discussed a variety of reasons why 1985 is a logical cutoff point for identifying the beginning of the globalization period. We also ran some formal tests to examine whether there exists a structural break in the sample. In particular, we perform some univariate break tests for a variance break following Stock and Watson (2005). We use the Andrews (1993) test for a break in either the unconditional variance or the persistence of each time series at an unknown date (see Appendix C for details). Searching over the middle 2/3 of the full time span of the sample, we find that 80 percent of those time series that have a break in their unconditional variance experience that break in or before 1984. A similar test for a break in the autoregressive parameter of a univariate AR(1) model also indicates that roughly 80 percent of the series that have a break have it by 1984. By choosing the 80 percent threshold, we are attempting to get as “clean” a look at the globalization period as possible. A break test on the entire multivariate factor model would be difficult to apply and beyond the scope of this paper. However, these simple univariate tests indicate that our break date of 1984 is reasonable. As a further robustness test, we estimated the full factor model based on break dates ranging from 1983 to 1987 and found nearly identical results, confirming that our results are not crucially dependent on the exact break date.

VII. Conclusion

In this paper, we have provided a comprehensive examination of the evolution of global business cycle linkages. We find that the global factor has become less important for macroeconomic fluctuations in both industrial economies and EMEs during the globalization period (1985-2005) relative to the pre-globalization period (1960-1984). By contrast, for both industrial countries and EMEs, the importance of group-specific factors has increased markedly. There has been little change in the degree of international synchronization of business cycles as measured by the joint contribution of the global and group-specific factors to explaining business cycles in the globalization period.

What are the implications of these results for the recent debate about whether there has been a global convergence or decoupling of national business cycles? Our findings suggest the need for a nuanced approach to this debate. Contrary to the convergence hypothesis, rising trade and financial integration are not associated with global convergence of business cycles, as evidenced by the decline in the importance of the global factor. But there is indeed some evidence of convergence at a different level. The increase in trade and financial linkages among industrial countries and among EMEs has been associated with the emergence of group-specific cycles. In other words, there has been a substantial convergence of business cycles among industrial economies and among EMEs, but there has also been a concomitant divergence or decoupling of business cycles between these two groups of countries.

Our findings should not be interpreted as a blanket endorsement of the decoupling hypothesis in the context of recent discussions about the possible spillover effects of a U.S. recession. Our results apply to a large set of industrial countries, not just the United States. Moreover, our study focuses on macroeconomic variables representing the real side of the economy, but leaves out financial ones.[25] In other words, our findings do not speak to the possibility of financial decoupling (or lack thereof). In any event, our results suggest that even

[25] Helbling et. al (2007) report that U.S. recessions are more worrisome for the rest of the world than a mid-cycle slowdown since U.S. import growth turns sharply negative during recessions, and cross-country asset price correlations increase significantly during financial market downturns.

the existence of large spillover effects across financial markets need not necessarily imply real spillovers of similar magnitude.

Changes in the relative importance of global and group-specific factors in driving national business cycles may be relevant for assessing the likely spillover effects of domestic shocks and the design of stabilization policies to counter them. However, existing theories have yet to provide clear guidance on these issues.[26]

[26] While international policy coordination serves an important role in an integrated world economy in the traditional models based on trade multiplier mechanisms, Obstfeld and Rogoff (2001) argue that increased integration may in fact diminish the need for monetary policy coordination. See Canzoneri, Cumby, and Diba (2005) for a survey.

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Appendix A. A Bayesian Approach to Estimating Dynamic Factor Models

The estimation procedure we use for our dynamic factor model is a Bayesian approach that exploits Gibbs sampling techniques. These techniques make it computationally feasible to draw from the exact finite sample distribution of the parameters and factors of interest in our model. The approach that we use builds upon the work of Otrok and Whiteman (1998) and does not rely on asymptotics in either the cross-sectional or the time dimension but at the same time is feasible from a computational standpoint for datasets where there are a large number of factors.

Our estimation procedure is better suited to answering the questions addressed in this paper than many of the alternatives. There are, of course, classical approaches to estimating dynamic factor models. Gregory et. al. (1997) follow Quah and Sargent (1993) and use Kalman filtering and the EM algorithm to estimate a dynamic factor model for the G-7 capturing the world as well as country specific cycles. Unfortunately, for a dataset of the dimension we are interested in (106 countries, 318 variables, and 110 factors), this approach is computationally infeasible. For very large datasets, such as ours, the approximate factor model approaches of Stock and Watson (1989) and Forni et. al. (1998) are quite efficient at extracting factors. However, the approximate factor models cannot be applied to situations where we wish to impose zero restrictions on some factor loadings to "identify" some factors as belonging to a particular country or a set of zero restrictions to limit other factors to a particular economy type. For example, we identify a country factor by having an unrestricted non-zero factor loading for all variables in that country. The variables of all other countries are restricted to have a zero factor loading on this country factor. The parametric approach we take can easily handle these restrictions.

Since analytic forms for the joint posterior of the factors and parameters are unobtainable, we employ numerical methods to simulate from the joint posterior distribution of the factors and parameters. We use a "data augmentation" algorithm to generate draws from the joint posterior of interest (see Tanner and Wong, 1987; Otrok and Whiteman, 1998). Data augmentation builds on the following key observation: if the factors were observable, under a conjugate prior, the model (1)-(3) would be a simple set of regressions with Gaussian autoregressive errors. Then, conditional on the regression parameters and the data, one can determine the conditional distribution of the factors. It is straightforward to generate random samples from this conditional distribution, and such samples can be employed as stand-ins for the unobserved factors.

To be more specific, the dynamic factor analysis model in equations (1)—(3) can be thought of as consisting of a specification of a Gaussian probability density for the data $\{y_t\}$ conditional on a set of parameters φ and a set of latent variables $\{f_t\}$. Call this density function $g_y(Y|\varphi,F)$ where Y denotes the $IJT \times 1$ vector of data on the observables, and F denotes the $M \times 1$ vector of dynamic factors. In addition, there is a specification of a Gaussian probability density $g_f(F)$ for F itself. Given a prior distribution for

φ, $\pi(\varphi)$, the joint posterior distribution for the parameters and the latent variables is given by the product of the likelihood and prior, $h(\varphi,F|Y) = g_y(Y|\varphi,F)g_f(F)\pi(\varphi)$. As is shown in Otrok and Whiteman (1998), although the joint posterior $h(\varphi,F|Y)$ is extremely cumbersome, under a conjugate prior for φ the two conditional densities $h(\varphi|F,Y)$ and $h(F|\varphi,Y)$ are quite simple. Moreover, it is possible to use this fact and Markov-Chain Monte Carlo methods (MCMC) to generate an artificial sample $\{\varphi_j,F_j\}$ for j = 1,…,J as follows:

1. Starting from a value F_0 in the support of the posterior distribution for F, generate a random drawing φ_1 from the conditional density $h(\varphi|F_0,Y)$.

2. Now generate a random drawing F_1 from the conditional density $h(F|\varphi_1,Y)$.

3. This process is repeated, generating at each step drawings $\varphi_j \sim h(\varphi|F_{j-1},Y)$ and $F_j \sim h(F|\varphi_{j-1},Y)$.

Under regularity conditions satisfied here (see Tanner and Wong, 1987), the sample so produced is a realization of a Markov chain whose invariant distribution is the joint posterior $h(\varphi,F|Y)$. What makes this process feasible is the simplicity of the two conditional distributions. For example, $h(\varphi|F,Y)$ is easily constructed from equation (1) when F is known. In particular, equation (1) is just a normal linear regression model for y_i given the factors (albeit a regression that has autocorrelated errors). Because the prior for the intercept and factor loadings is Gaussian, the conditional posterior for the parameters (σ_i, a_i and the b_i's) is also Gaussian. The other conditional density, $h(F|\varphi,Y)$ is a little more complicated because it is the solution to a Gaussian signal extraction problem. Kalman filter techniques are commonly used to solve such problems, but when the time series is short, as in this application, it is straightforward to solve the problem directly. Solving the problem without using the Kalman filter is especially useful when the number of factors is large, as in the problem we study. (With a large number of factors the state equation in the Kalman filter can become computationally very burdensome.) Otrok and Whiteman (1998) do this as follows: first, they write the joint density for the data and the dynamic factors given the parameters as a product of I*J*M independent Gaussian densities (I*J of them are associated with the observable time series, M with the dynamic factors). Second, from this joint distribution, simple normal distribution theory is used to obtain the conditional distribution for any one of the factors given the rest and the parameters. These normal distributions involve inverses of $T \times T$ covariance matrices that can be handled using conventional procedures provided T is not large. In the model analyzed here, $T = 40$ is not problematic.

The prior on all the factor loading coefficients is N(0,10), which is quite diffuse. For the parameters of autoregressive polynomials, the prior is $N(0,\Sigma)$, where $\Sigma=\begin{bmatrix} 1 & 0 & 0 \\ 0 & .5 & 0 \\ 0 & 0 & .25 \end{bmatrix}$. Because the data are growth rates, this prior embodies the notion that growth is not serially correlated though the prior is loose enough to allow for significant serial correlation; also, the probability that lags are zero grows with the length of the lag.[27] Experimentation with tighter and looser priors for both the factor loadings and the autoregressive parameters did not produce qualitatively important changes in the results reported below. The prior on the innovation variances in the observable equations is Inverted Gamma (6, 0.001), which is also quite diffuse.

Since we are not sampling from the posterior itself (the elements of the Markov chain are converging to drawings from the posterior), it is important to monitor the convergence of the chain. We do so in a number of ways. First, we restarted the chain from a number of different initial values, and the procedure always converged to the same results. Second, we experimented with chains of different lengths ranging from lengths of 2,500 to 10,000. The results remained unchanged. The results we report are based on a chain of length 5,000.

[27] Otrok and Whiteman (1998) discuss the procedure for ensuring stationarity of the lag polynomial. The method involves drawing from a truncated Normal distribution in the Metropolis-Hastings step.

Appendix B: Testing for Structural Breaks

There is substantial evidence of structural breaks in many macroeconomic time series. One approach to identifying structural breaks in our model would be to specifically allow for breaks in the factor loadings, innovation terms and autoregressive parameters in the model described by equations (1)-(3). Unfortunately, given the size of our model the econometric implementation of such a procedure is infeasible. Instead, we use a sequence of univariate break tests to shed light on the potential for breaks in the data. The tests we use consider breaks in both persistence and volatility and allow for one break at an unknown date for each variable (Andrews 1991).

The first test we employ estimates an AR(1) model to each time series and tests for a break in both the constant term and autoregressive parameter. The Andrews test requires us to estimate the model over the whole sample and then again allowing for a break at each possible date. That is we estimate:

$$y_t = a + D(s) + \rho y_{t-1} + D(s)\alpha y_{t-1} + \varepsilon_t$$

where D(s) is a dummy variable that takes the value 0 before the break date and 1 at the break date (s = t) and all dates after the break date. For each possible break date we estimate the model in (4) and calculate the Wald statistic:

k*((SSR-SSU)/k)/(SSU/(T-2*k))

where SSR is the sum of squared residuals from the regression with no break (D(s) = 0 for all t) and SSU is the sum of squared residuals for the regression that allows for a break. K is the number of parameters that may break, in our case k = 2. T is the number of time series observations. We calculate the Wald statistic for all possible break dates in the middle 2/3 of the sample, since tests near the endpoints have been known to be unreliable, and use the max of the Wald statistics as our potential break date. The statistical significance of this break can be checked against the critical values provided in Andrews (1991), which depend on S/T.

To test for a break in only the volatility in each series, we regress the demeaned absolute value of each series on a constant for the restricted regression and then on a constant and a dummy variable for the unrestricted regression. That is, for the unrestricted regression we estimate:

$$y_t{}^* = a + D(s) + \varepsilon_t$$

where y_t* is the demeaned absolute value of the series, for all possible break dates. The Wald statistic is as given above with k = 1 degrees of freedom.

Appendix C: List of Countries

Groups of Countries			
INDUSTRIAL	EMERGING MARKETS	OTHER DEVELOPING COUNTRIES	
Australia	Argentina	Burundi	Sri Lanka
Austria	Brazil	Benin	Lesotho
Belgium	Chile	Burkina Faso	Madagascar
Canada	China	Bangladesh	Mali
Switzerland	Colombia	Bolivia	Mozambique
Denmark	Egypt, Arab Rep.	Barbados	Mauritania
Spain	Hong Kong, China	Botswana	Mauritius
Finland	Indonesia	Cote d'Ivoire	Malawi
France	India	Cameroon	Niger
United Kingdom	Israel	Congo, Rep.	Nigeria
Germany	Jordan	Comoros	Nicaragua
Greece	Korea, Rep.	Cape Verde	Nepal
Ireland	Morocco	Costa Rica	Panama
Iceland	Mexico	Dominican Republic	Paraguay
Italy	Malaysia	Algeria	Rwanda
Japan	Pakistan	Ecuador	Senegal
Luxembourg	Peru	Ethiopia	El Salvador
Netherlands	Philippines	Gabon	Seychelles
Norway	Singapore	Ghana	Syrian Arab Republic
New Zealand	Thailand	Guinea	Chad
Portugal	Turkey	Gambia, The	Togo
Sweden	Taiwan	Guinea-Bissau	Trinidad and Tobago
United States	Venezuela, RB	Equatorial Guinea	Tunisia
	South Africa	Guatemala	Tanzania
		Guyana	Uganda
		Honduras	Uruguay
		Haiti	Congo, Dem. Rep.
		Iran, Islamic Rep.	Zambia
		Jamaica	Zimbabwe
		Kenya	

Data sources: Primarily from the World Bank's World Development Indicators (WDI), supplemented with the International Monetary Fund's World Economic Outlook (WEO) database.

Table 1
Variance Decompositions
All Groups
(1960-2005)

Group	Factor	Output	Consumption	Investment
World	Global	11.48	8.58	5.51
	Group	5.22	2.79	5.39
	Global+Group	16.70	11.37	10.90
	Country	46.75	39.70	30.90
	Idiosyncratic	35.31	47.80	57.04
Industrial Countries	Global	27.10	24.30	12.13
	Group	13.40	5.89	15.63
	Global+Group	40.51	30.19	27.76
	Country	38.64	34.88	40.76
	Idiosyncratic	20.28	34.17	30.85
Emerging Market Economies	Global	7.85	4.84	3.89
	Group	6.27	3.52	4.74
	Global+Group	14.12	8.36	8.63
	Country	60.30	39.77	46.97
	Idiosyncratic	24.56	51.01	43.46
Other Developing Countries	Global	6.88	3.97	3.59
	Group	1.60	1.29	1.66
	Global+Group	8.48	5.27	5.26
	Country	44.40	41.55	20.52
	Idiosyncratic	45.55	51.81	72.78

Notes: We estimate the model over the full sample period (1960-2005) and compute the variance decompositions for each country and, within each country, for output, consumption and investment. In each cell, we then report the cross-sectional mean of the variance share attributable to the relevant factor. The cross-sectional means are calculated for the relevant cluster of countries indicated in the first column. The rows marked (Global+Group) are just the sums of the average variance shares of the global and group-specific factors.

Table 2
Variance Decompositions
Industrial Country Subsamples
(1960-2005)

Group	Factor	Output	Consumption	Investment
Industrial Countries	Global	27.10	24.30	12.13
	Group	13.40	5.89	15.63
	Global+Group	40.51	30.19	27.76
	Country	38.64	34.88	40.76
	Idiosyncratic	20.28	34.17	30.85
G-7	Global	35.74	33.00	17.00
	Group	10.35	5.49	16.33
	Global+Group	46.09	38.49	33.33
	Country	38.47	36.96	45.73
	Idiosyncratic	14.89	23.84	20.20
US-Canada	Global	22.62	25.28	6.21
	Group	4.24	1.10	1.82
	Global+Group	26.86	26.38	8.02
	Country	53.83	51.32	69.83
	Idiosyncratic	18.69	21.60	21.30
EU 12	Global	36.67	31.50	16.56
	Group	14.81	5.46	18.38
	Global+Group	51.48	36.96	34.94
	Country	28.81	25.25	34.86
	Idiosyncratic	19.10	36.97	29.56

Notes: We estimate the model over the full sample period (1960-2005) and compute the variance decompositions for each country and, within each country, for output, consumption and investment. In each cell, we then report the cross-sectional mean of the variance share attributable to the relevant factor. The cross-sectional means are calculated for the relevant cluster of countries indicated in the first column. The rows marked (Global+Group) are just the sums of the average variance shares of the global and group-specific factors.

Table 3
Variance Decompositions
All Groups

		1960-1984			1985-2005		
Group	**Factor**	**Output**	**Consumption**	**Investment**	**Output**	**Consumption**	**Investment**
World	Global	14.67	10.94	7.14	7.03	5.28	5.89
	Group	5.66	4.33	5.62	10.69	8.04	9.95
	Global+Group	20.33	15.27	12.76	17.72	13.32	15.84
	Country	43.99	39.14	28.60	42.10	36.21	34.51
	Idiosyncratic	33.31	43.09	56.21	35.17	46.06	45.10
Industrial Countries	Global	27.68	25.27	12.06	9.36	10.59	9.63
	Group	17.16	9.39	15.29	31.27	23.54	28.04
	Global+Group	44.84	34.66	27.35	40.62	34.13	37.67
	Country	33.34	32.13	39.25	31.69	24.57	34.65
	Idiosyncratic	20.66	31.72	31.88	23.71	37.09	24.35
Emerging Market Economies	Global	13.28	7.22	6.38	4.20	3.71	3.80
	Group	2.65	3.84	3.13	9.31	6.04	9.80
	Global+Group	15.93	11.06	9.52	13.51	9.75	13.60
	Country	53.40	36.38	39.57	61.39	46.23	51.24
	Idiosyncratic	28.56	50.50	48.63	21.26	40.06	31.51
Other Developing Countries	Global	10.16	6.86	5.53	7.28	3.86	5.28
	Group	2.40	2.56	2.86	3.22	2.81	2.96
	Global+Group	12.56	9.42	8.40	10.50	6.67	8.24
	Country	44.32	43.00	19.99	38.31	36.67	27.66
	Idiosyncratic	40.17	44.50	68.79	45.29	52.01	58.72

Notes: We estimate the model separately over the two periods, 1960-1984 and 1985-2005. We then compute the variance decompositions for each country and, within each country, for output, consumption and investment in each of these two periods. In each cell, we then report the cross-sectional mean of the variance share attributable to the relevant factor. The cross-sectional means are calculated for the relevant cluster of countries indicated in the first column. The rows marked (Global+Group) are just the sums of the average variance shares of the global and group-specific factors.

Table 4
Variance Decompositions
Industrial Country Subsamples

		1960-1984			1985-2005		
Group	**Factor**	**Output**	**Consumption**	**Investment**	**Output**	**Consumption**	**Investment**
Industrial Countries	Global	27.68	25.27	12.06	9.36	10.59	9.63
	Group	17.16	9.39	15.29	31.27	23.54	28.04
	Global+Group	44.84	34.66	27.35	40.62	34.13	37.67
	Country	33.34	32.13	39.25	31.69	24.57	34.65
	Idiosyncratic	20.66	31.72	31.88	23.71	37.09	24.35
G-7	Global	36.87	36.20	16.14	12.26	15.37	11.51
	Group	14.42	9.27	17.03	31.67	21.89	33.33
	Global+Group	51.29	45.47	33.17	43.94	37.26	44.84
	Country	32.02	30.05	42.78	32.86	32.75	37.07
	Idiosyncratic	15.57	23.01	22.43	19.19	25.71	14.94
US-Canada	Global	35.17	39.99	12.90	13.12	21.69	12.39
	Group	1.93	1.20	0.97	12.49	7.80	8.11
	Global+Group	37.10	41.19	13.87	25.61	29.49	20.50
	Country	43.50	37.15	65.85	47.52	39.78	60.63
	Idiosyncratic	18.42	20.18	18.63	22.67	26.17	14.96
EU 12	Global	34.81	30.56	15.48	7.30	8.61	9.05
	Group	18.46	7.41	18.31	45.14	33.48	37.16
	Global+Group	53.27	37.98	33.79	52.44	42.09	46.21
	Country	26.50	26.71	34.55	22.85	17.11	26.28
	Idiosyncratic	19.13	33.78	30.15	21.23	37.06	24.55

Notes: We estimate the model separately over the two periods, 1960-1984 and 1985-2005. We then compute the variance decompositions for each country and, within each country, for output, consumption and investment in each of these two periods. In each cell, we then report the cross-sectional mean of the variance share attributable to the relevant factor. The cross-sectional means are calculated for the relevant cluster of countries indicated in the first column. The rows marked (Global+Group) are just the sums of the average variance shares of the global and group-specific factors.

Table 5
Variance Decompositions
Emerging Economy Subsamples

		1960-1984			1985-2005		
Group	**Factor**	**Output**	**Consumption**	**Investment**	**Output**	**Consumption**	**Investment**
Emerging Market Economies	Global	13.28	7.22	6.38	4.20	3.71	3.80
	Group	2.65	3.84	3.13	9.31	6.04	9.80
	Global+Group	15.93	11.06	9.52	13.51	9.75	13.60
	Country	53.40	36.38	39.57	61.39	46.23	51.24
	Idiosyncratic	28.56	50.50	48.63	21.26	40.06	31.51
Emerging Asia	Global	10.01	6.26	5.72	3.80	3.72	4.52
	Group	3.51	3.77	4.22	9.99	5.45	9.36
	Global+Group	13.52	10.03	9.94	13.78	9.17	13.88
	Country	49.32	30.85	33.69	56.38	41.73	49.07
	Idiosyncratic	34.92	56.99	53.95	26.00	44.92	33.06
Emerging Asia 10	Global	12.31	9.05	6.41	3.65	3.71	4.27
	Group	3.88	3.95	4.46	10.78	7.15	9.88
	Global+Group	16.19	13.00	10.87	14.43	10.86	14.15
	Country	53.48	31.90	39.91	61.94	46.60	54.34
	Idiosyncratic	28.24	53.08	46.74	19.70	38.10	27.65
Emerging Latin America	Global	22.97	11.11	9.15	4.45	3.82	2.69
	Group	1.24	4.52	1.43	9.70	8.66	10.08
	Global+Group	24.21	15.63	10.58	14.15	12.48	12.78
	Country	57.68	42.10	50.09	69.96	47.58	60.93
	Idiosyncratic	16.18	40.33	37.29	12.31	36.35	23.34
Emerging Africa	Global	3.95	0.91	1.68	6.31	3.27	2.29
	Group	1.09	1.93	0.96	2.88	1.23	12.05
	Global+Group	5.04	2.85	2.65	9.19	4.51	14.34
	Country	69.02	57.85	46.86	68.94	75.34	33.53
	Idiosyncratic	24.20	37.46	48.48	17.03	16.54	48.51

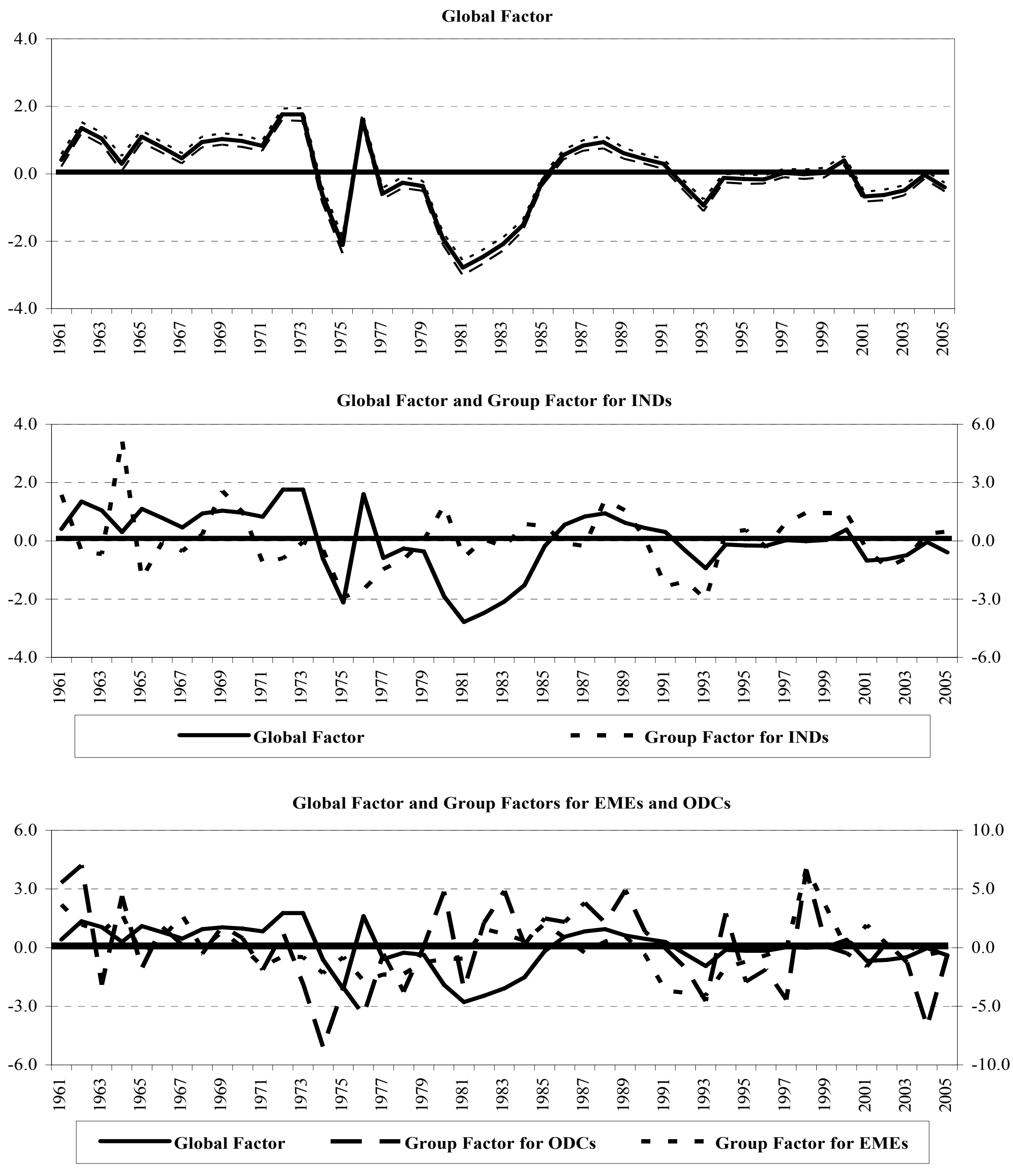
Notes: We estimate the model separately over the two periods, 1960-1984 and 1985-2005. We then compute the variance decompositions for each country and, within each country, for output, consumption and investment in each of these two periods. In each cell, we then report the cross-sectional mean of the variance share attributable to the relevant factor. The cross-sectional means are calculated for the relevant cluster of countries indicated in the first column. The rows marked (Global+Group) are just the sums of the average variance shares of the global and group-specific factors.

Table 6
Variance Decompositions
Other Developing Economy Subsamples

		1960-1984			1985-2005		
Group	**Factor**	**Output**	**Consumption**	**Investment**	**Output**	**Consumption**	**Investment**
Other Developing Economies	Global	10.16	6.86	5.53	7.28	3.86	5.28
	Group	2.40	2.56	2.86	3.22	2.81	2.96
	Global+Group	12.56	9.42	8.40	10.50	6.67	8.24
	Country	44.32	43.00	19.99	38.31	36.67	27.66
	Idiosyncratic	40.17	44.50	68.79	45.29	52.01	58.72
Developing Asia	Global	4.15	3.34	0.50	10.43	4.50	8.85
	Group	1.69	3.07	1.88	2.81	2.20	2.32
	Global+Group	6.37	6.44	2.38	13.12	7.34	11.40
	Country	60.83	59.63	20.69	43.98	27.52	40.28
	Idiosyncratic	30.53	31.15	74.55	37.12	60.70	42.54
Developing Latin America	Global	18.25	12.74	7.94	8.73	4.24	4.74
	Group	2.61	2.05	3.36	3.10	1.94	2.03
	Global+Group	20.86	14.79	11.30	11.83	6.18	6.77
	Country	44.45	46.41	29.15	37.22	35.34	34.56
	Idiosyncratic	31.79	35.95	56.48	45.13	53.62	53.70
Developing Africa	Global	7.47	4.84	5.18	6.27	3.53	5.00
	Group	2.40	2.70	2.79	3.32	3.26	3.44
	Global+Group	10.09	7.66	8.11	9.59	6.86	8.50
	Country	42.09	39.38	16.05	38.02	38.43	23.09
	Idiosyncratic	44.97	49.86	73.21	46.43	50.18	62.97

Notes: We estimate the model separately over the two periods, 1960-1984 and 1985-2005. We then compute the variance decompositions for each country and, within each country, for output, consumption and investment in each of these two periods. In each cell, we then report the cross-sectional mean of the variance share attributable to the relevant factor. The cross-sectional means are calculated for the relevant cluster of countries indicated in the first column. The rows marked (Global+Group) are just the sums of the average variance shares of the global and group-specific factors.

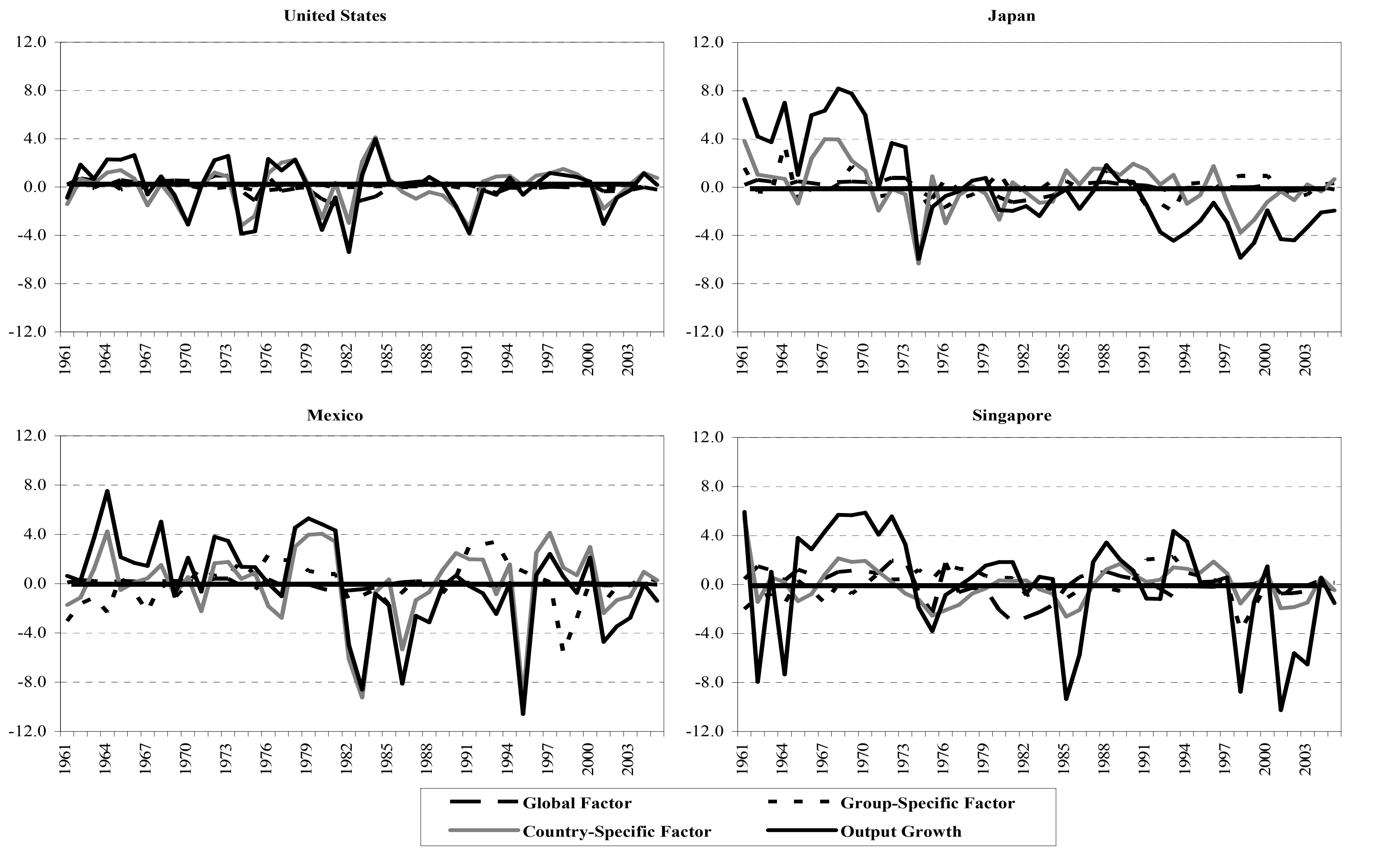
Figure 1
Global and Group-Specific Factors



Notes: In the top panel, we estimate the model over the full sample period and then plot the mean of the posterior distribution of the estimated global factor (the dark solid line). The dashed/dotted lines around the mean show 5 percent and 95 percent quantile bands of the distribution of estimates of the global factor. In the middle and bottom panels, we estimate the model over the full sample period and then plot the mean of the posterior distribution of the estimated factors. INDs, EMEs and ODCs refer to Industrial Countries, Emerging Market Economies and Other Developing Countries, respectively.

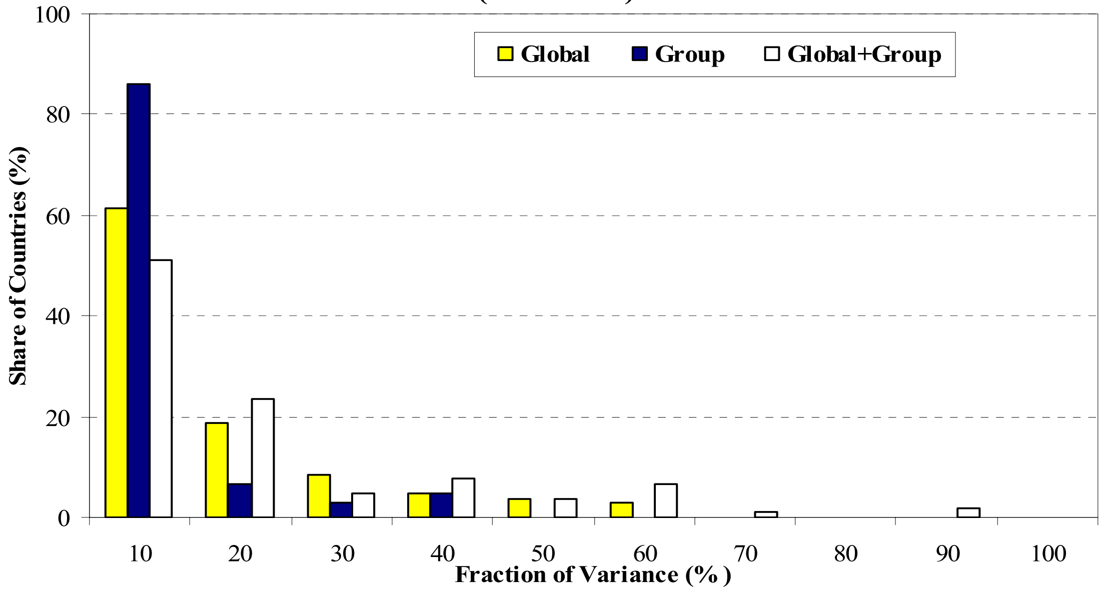
Figure 2

Output Growth and Estimated Factors for Selected Countries



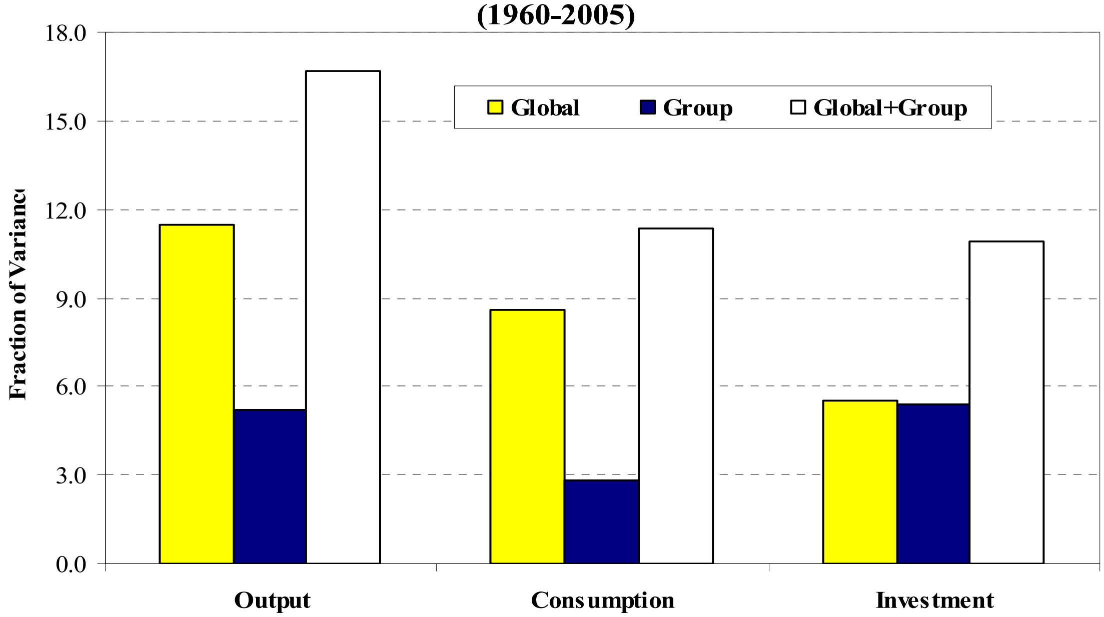
Notes: We estimate the model over the full sample period. For the relevant country in each plot, we then show the means of the posterior distributions for each of the factors, along with overall annual output growth for that country.

Figure 3
Average Variance Explained by the Global and Group Factors
(1960-2005)



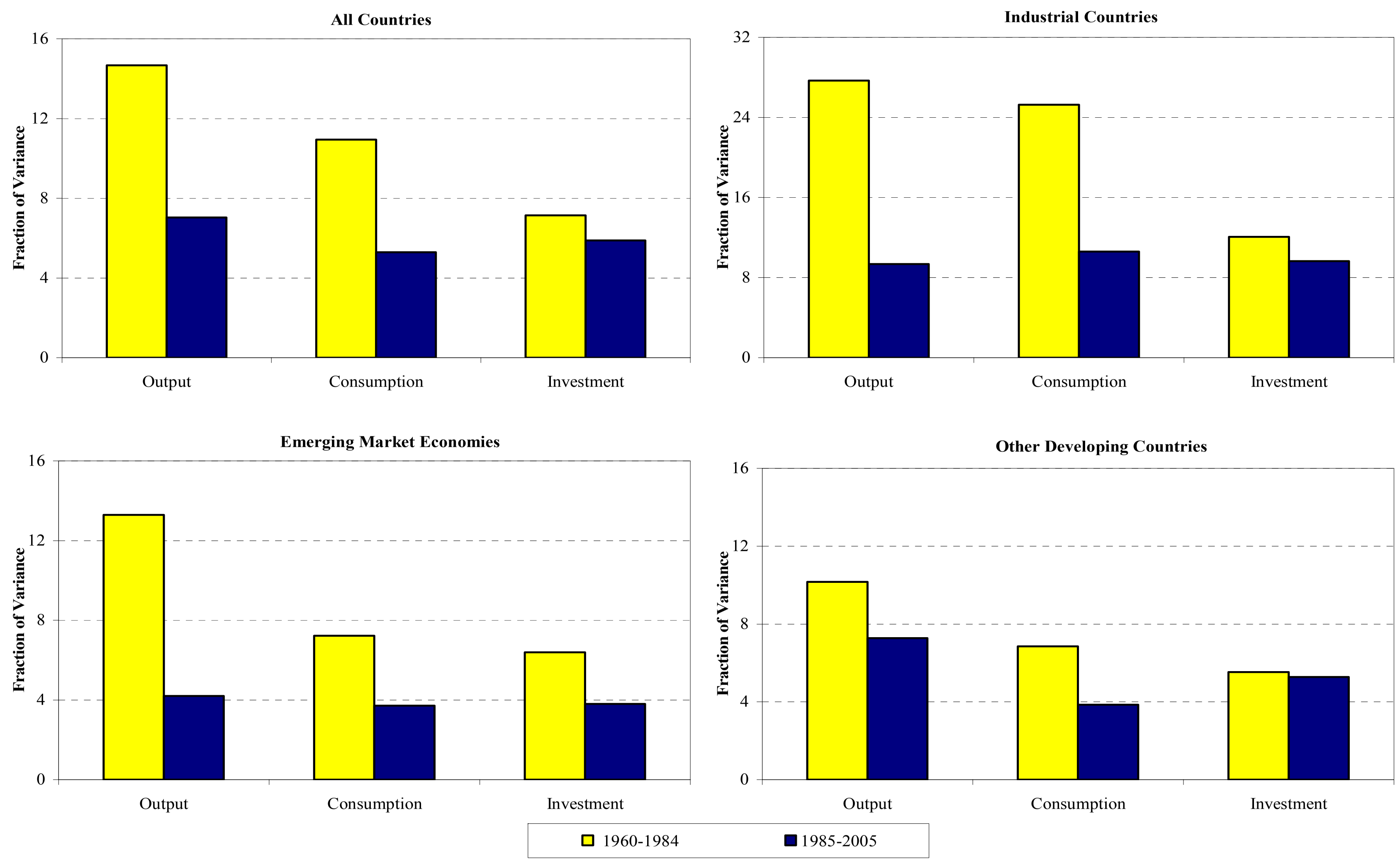
Notes: We estimate the model over the full sample period and then compute the variance shares of the two common factors in our model (global and group-specific) for each country. This plot shows the frequency distribution of countries for which the total contribution share of the two common factors is in the range of 0-10 percent, 10-20 percent etc.

Figure 4
Average Variance Explained by Global and Group Factors
(1960-2005)



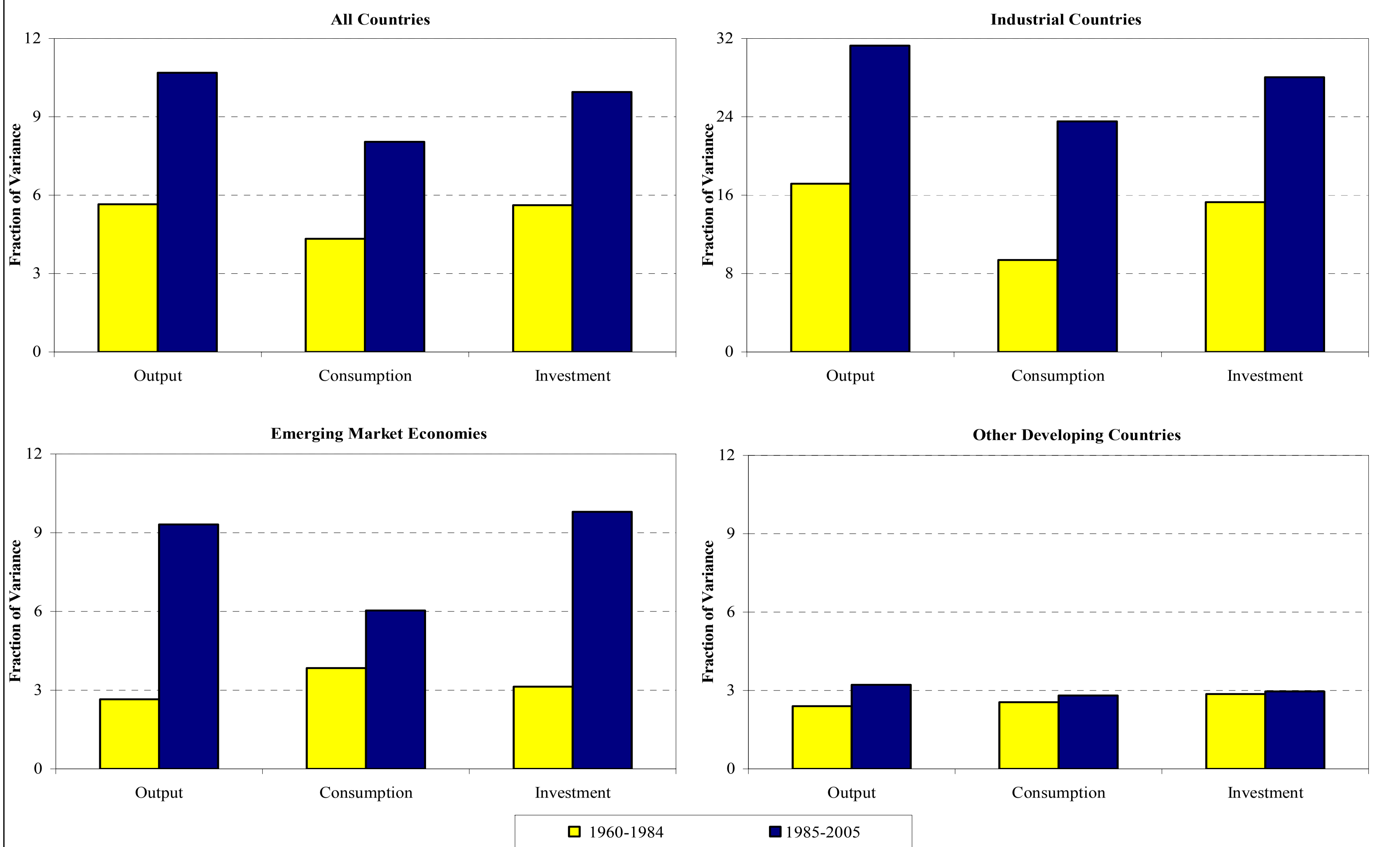
Notes: We estimate the model over the full sample period (1960-2005) and compute the variance decompositions for each country and, within each country, separately for output, consumption and investment. Each bar then represents the cross-sectional mean of the variance share attributable to the relevant factor for that particular variable. The cross-sectional means are calculated over the full sample of countries. The bar marked (Global+Group) represents the sum of the average variance shares of the global and group-specific factors for each variable.

Figure 5
Average Variance Explained by Global Factor



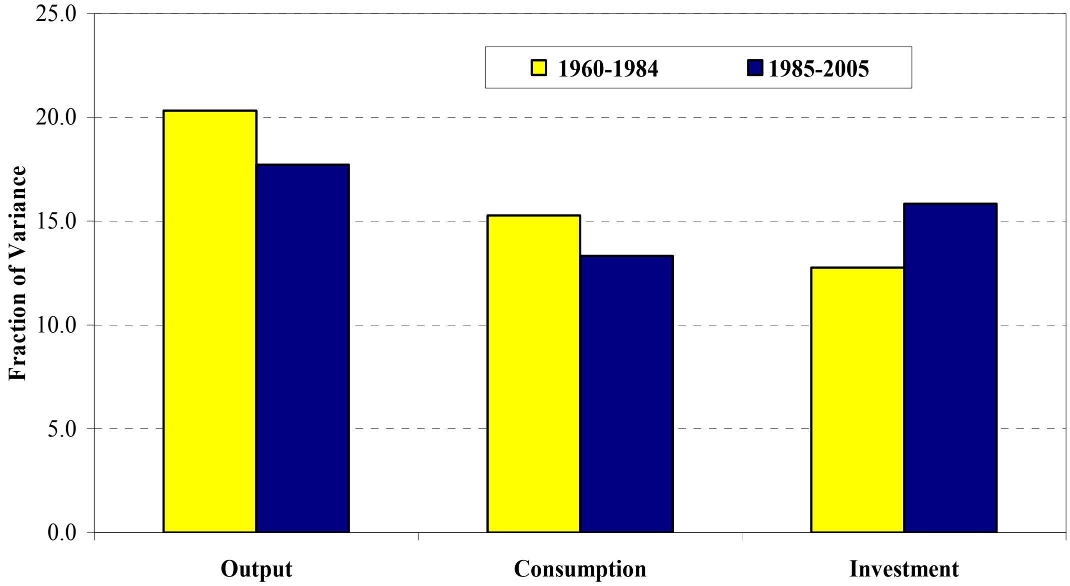
Notes: We estimate the model separately over the two periods, 1960-1984 and 1985-2005. We then compute the variance decompositions for each country and, within each country, for output, consumption and investment in each of these two periods. Each bar then represents the cross-sectional mean of the variance share attributable to the global factor for that particular variable in a given period. The cross-sectional means are calculated over the relevant group of countries.

Figure 6
Average Variance Explained by Group-Specific Factors



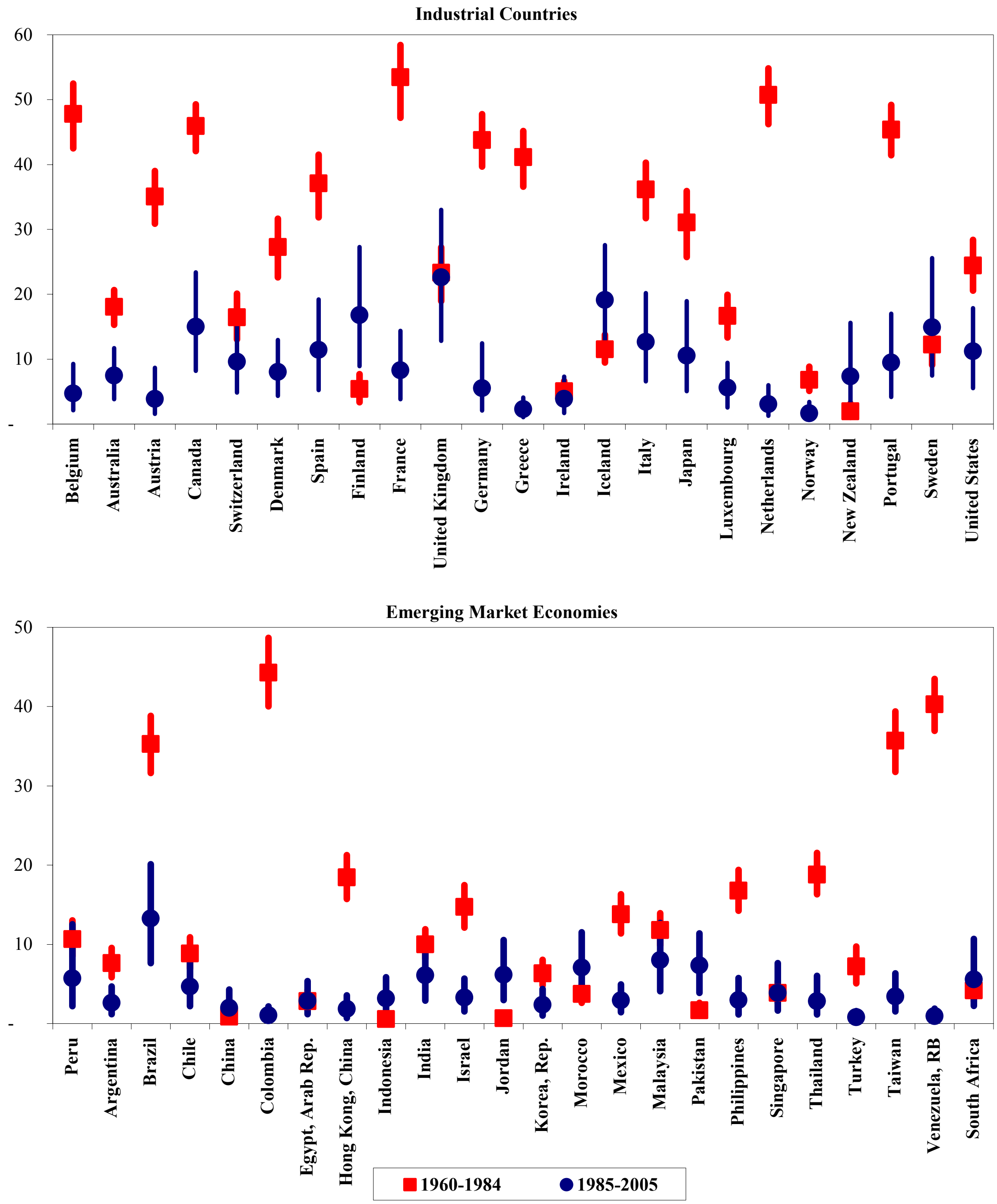
Notes: See Notes to Figure 5.

Figure 7
Average Variance Explained by Global and Group-Specific Factors
All Countries



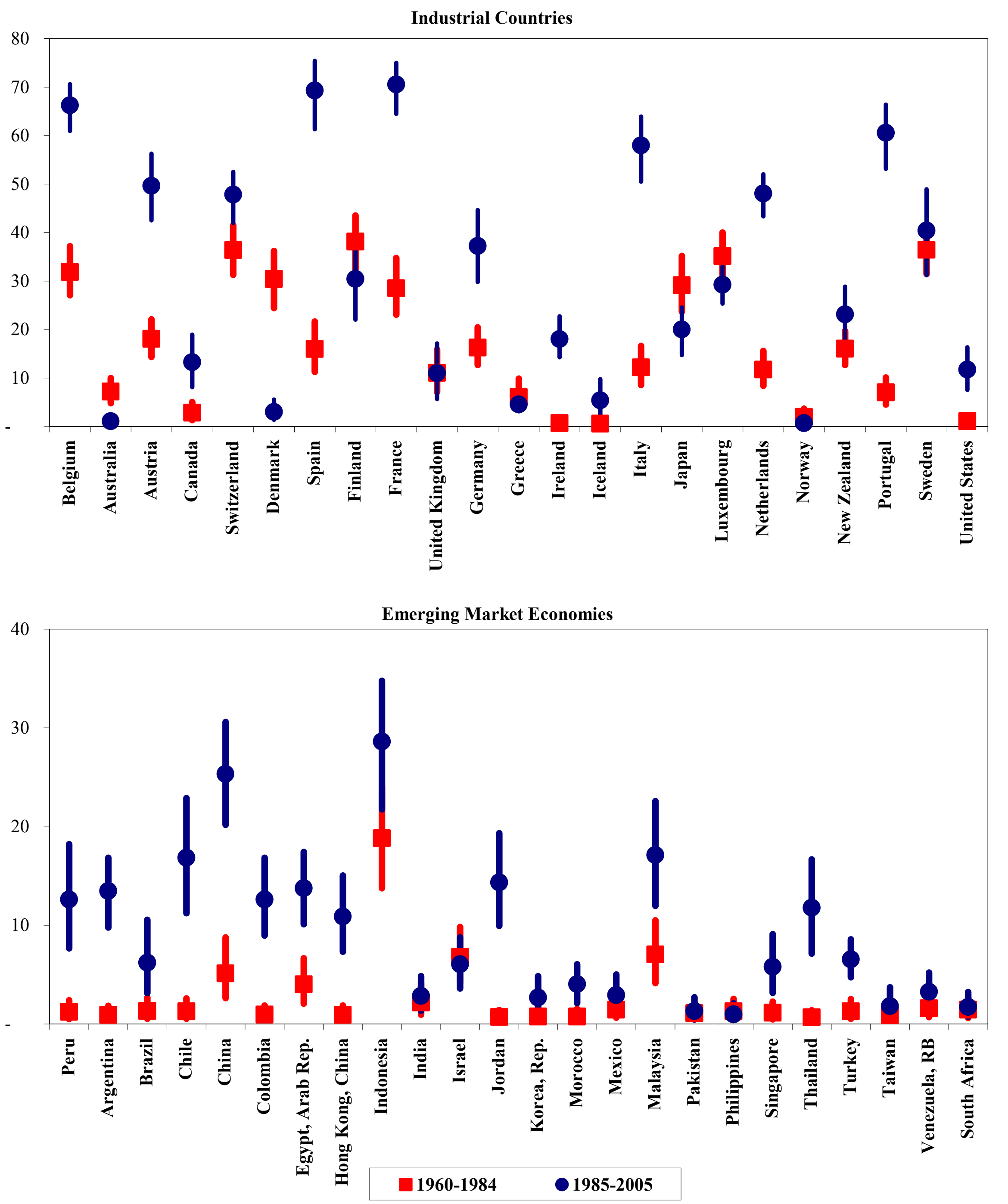
Notes: We estimate the model separately over the two periods, 1960-1984 and 1985-2005. We then compute the variance decompositions for each country and, within each country, for output, consumption and investment in each of these two periods. Each bar then represents the cross-sectional mean of the variance share attributable to the sum of global and group-specific factors for that particular variable in a given period. The cross-sectional means are calculated over the full set of countries in our sample.

Figure 8
Output Variance Explained by Global Factor



Notes: We estimate the model separately over the two periods, 1960-1984 and 1985-2005. For each country, we then show the posterior means of the share of the variance of output growth fluctuations accounted for by the relevant factor in each panel. We also show the corresponding posterior coverage intervals of length two standard deviations (%).

Figure 9
Output Variance Explained by Group Factor



Notes: See notes to Figure 8.