Business Cycle Synchronization: A Bayesian Model of Survey Forecasts

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Abstract
Using real GDP growth forecasts, we measure the impact of business cycle synchronization on industrialized countries and Asia developing economies. Our measures are based on a Bayesian time-varying parameter dynamic factor model of the forecast revisions. Empirical results highlight a significant amount of global spillovers of real economic shocks from industrialized countries, while a regional business cycle in Asia is as important as the global cycle to developing economies. We find no evidence of permanent shifts in the degree of business cycle synchronization. Instead, transient shocks play a dominant role in the last 20 years.

Keywords: real GDP growth, dynamic factor model, time-varying parameters

1. Introduction

Driven by the expansion of international trade and the increased level of financial market integration, global business cycle synchronization has become the focal point of a large body of literature in the last 20 years. Understanding its evolution is of great importance to today's researchers and policymakers.

Despite the volume of research devoted to this issue, a widely accepted conclusion regarding the level of synchronization and its recent structural changes has yet to emerge, especially when developing economies are concerned.[1] In a recent work, Lahiri and Zhao (2017) use a factor structural vector auto regression model of survey forecasts to document the changing patterns of international transmission of real economic shocks. Their results, while confirming the findings in the literature regarding increased convergence within the group of industrialized countries and that of developing economies, highlight the time-varying nature of business cycle synchronizations. More specifically, they find systematic difference in the impact of shocks during crisis and non-crisis periods.

This paper extends the work of Lahiri and Zhao (2017) by specifically modeling the variation over time in an economy's integration in regional and global business cycles using the Bayesian time-varying parameter dynamic factor model first employed by Del Negro and Otrok (2008). We use the same data set as used in Lahiri and Zhao (2017), which contains monthly forecasts of annual rate of growth for 16 industrialized and developing economies in North America, Europe, and Asia. As established in Lahiri and Zhao (2017), since these forecasts are efficient in the long-run, inferences based on the forecasts coincide

[1] Many authors have looked into this and closely related issues. Some recent examples include Agenor *et al.* (2000), Canova (2005), Del Negro and Otrok (2008), Bordo and Helbling (2011), Kose *et al.* (2012), Abiad *et al.* (2013), Andrle *et al.* (2013), Comin *et al.* (2014), Duval *et al.* (2014), Didier *et al.* (2016), Huidrom *et al.* (2017), Lahiri and Zhao (2017), and Park (2017).

with those based on official statistics. The revisions of these forecasts act as natural measures of economic news observed in real time. Using a sample from January 1995 to December 2017, we examine the evolution of correlations between the forecast revisions for different economies, estimate the global and the Asia regional business cycles, and quantify the exposure of different economies to these common cycles.

We find the global and the Asia regional business cycle to be consistent with our understanding of the impact of recent regional and global financial and economic crisis. Both the industrialized economies and the developing economies have significant exposure to these common cycles. However, the global business cycle dominated by industrialized countries does not have a bigger impact on Asia developing economies than that of the regional business cycle. In addition, while we document extensive fluctuations in business cycle synchronization, we do not have evidence of permanent shifts in the degree of co-movements. Instead, the last 20 years have witnessed the dominance of transient shocks, which are mostly due to financial and economic crisis.

The multi-horizon fixed-target survey forecasts are introduced in the next section. Section 3 presents the time varying parameter dynamic factor model and discusses the implications of its assumptions. Empirical results are reported in Section 4. Section 5 concludes.

2. Consensus Forecasts

We use real GDP growth forecasts published by Consensus Economics Inc. in two of their publications. The forecasts for major industrialized countries are published in the *Consensus Forecasts - G7 & Western Europe*. The forecasts for the other countries in our sample are from the *Asia Pacific Consensus Forecasts*. In these publications, forecasts from individual entities, such as government agencies, consulting firms, and research institutions, are available on a monthly basis. We take the average of the forecasts with the same target to form a time series for each country.[2] The following 16 countries and regions are in our sample: United States, Japan, India, China, United Kingdom, France, Germany, Italy, Hong Kong, South Korea, Taiwan, Indonesia, Malaysia, Philippines, Singapore, and Thailand.

From each month between January 1995 and December 2016, we have two forecasts for each country. The first forecast targets the current year and the second the next year. Within a year, the targets are fixed.[3] From January to December, the forecast horizon of the first forecast declines from 12 months to 1 month and that of the second forecast goes from 24 months to 13 months. For each country, we organize our data by target year: a time series of 24 forecasts with declining horizons is available for each target year. There is a gap in the time series at each change of the target year.[4]

We plot the forecasts for the United States in Figure 1, which clearly shows how the forecasts evolve as more information becomes available as horizon shortens. The two-year-

[2] The number of forecasts available varies across countries and over time. A list of the forecasters can be found in Table 1 of Lahiri and Zhao (2017).
[3] For example, in December 2015, the first forecast is for the annual real GDP growth rate of 2015, and the second for that of 2016. Come January 2016, the first forecast targets 2016 and the second 2017. The target years of the two forecasts remain the same throughout 2016, before they each increment by one year starting from January 2017.
[4] Obviously, forecasts with horizons 24 to 13 for 1995 and those with horizons 12 to 1 for 2017 are not available.

ahead forecasts almost always fall within the interval of 2 to 4%, reflecting forecasters' belief on a stable long-run growth rate. As time goes by, forecasts are revised to reflect the availability of new information relevant to the specific target years.[5] As a result, the forecasts become more divergent. This is particularly obvious in the bottom plot of Figure 1. A significant downward revision was made to the forecast of 2009 sixteen months ahead, when the impact of the 2008 recession became clear.

By examining the forecast revisions, we obtain direct measures of economic news. As an illustration, Figure 2 plots the forecast revisions of the United States. These are simply the first differences in the forecasts reported in Figure 1. But instead of organizing them by target year, we plot the time series separately for current-year forecasts and next-year forecasts. This way, we can get a clear picture of the real-time influx of economic news throughout our sample period. The top plot in Figure 2 shows the current-year forecast revisions. Compared with the next-year forecast revisions in the bottom plot, we can clearly see that most new information comes within the year, as the amount of variation in the forecast revisions is significantly bigger in the top plot – except when there is a recession, as illustrated by the two large negative revisions in the bottom plot. Using forecast revisions as a measure of news in real time, we can model real shocks to an economy at a higher frequency and level of accuracy than that allowed by using official real GDP statistics.

In order to avoid having to estimate unnecessarily large models, as an empirical strategy, we form the following three country groups:[6] Europe (United Kingdom, France, Germany, and Italy), Northeast Asia (Hong Kong, South Korean, and Taiwan), and Southeast Asia (Indonesia, Malaysia, Philippines, Singapore, and Thailand). These three groups, along with the United States, Japan, China, and India, are considered in subsequent analysis. For each group, we construct a weighted average of the forecasts for its members and treat this weighted average as the forecast for the group. A country's weight in a group is the share of its GDP relative to the total GDP of the member countries of the group. As usual, forecast revisions for each group are calculated as the first difference of the forecasts for the group.[7]

In order for the forecast revisions to be valid estimates of news or shocks to the economy, the forecasts need to be efficient, in the sense that all relevant news must be used by the forecasters. However, as established in Lahiri and Zhao (2017), our inferences based on forecasts are valid even under the weaker assumption of long-run forecast efficiency: Instead of requiring that every single forecast contains all the historical information available up to the time when the forecast is made, all we need to assume is that this information is eventually fully utilized as the forecast is repeatedly revised. Using the same data set as ours, Lahiri and Zhao (2017) carefully measured the efficiency of the forecasts and concluded that it takes no more than six months for news to be fully utilized by the

[5] Since the forecasts we are using are the consensus rather than the work of one individual forecaster, revisions to the forecasts reflect not the idiosyncrasies across forecasters but the news available to all forecasters.
[6] The decision on which countries to group together is based on bilateral trade relationships which are known to be correlated with business cycles ((Baxter and Kouparitsas (2005))). Subsequently, we may simply refer to a country group as a country where no confusion could arise.
[7] Member countries' GDPs are based on official statistics and are measured as chained purchasing power parities in 2005 dollars. The weights are updated once every year. The same strategy is employed by Lahiri and Zhao (2017), whose Table 2 lists the weights for each country in each year.

forecasters.[8] Given that we have a much longer time series of forecasts for each target year, it is reasonable to maintain the assumption of long-run forecast efficiency. For brevity, we do not repeat these analysis in this paper.

3. A Time-Varying Parameter Dynamic Factor Model

With i being the country index ($i \in \{1, 2, 3, \dots, J\}$) and h the forecast horizon ($h > 0$), let $y_{i,t,h}$ be the forecast of real GDP growth, whose difference, $r_{i,t,h} \equiv y_{i,t,h} - y_{i,t,h+1}$ is the associated forecast revision. Under the weak assumption of long-run forecast efficiency, a revision may reflect both current and historical information:

$$r_{i,t,h} = \beta_0 \varepsilon_{i,t,h} + \beta_1 \varepsilon_{i,t,h+1} + \beta_2 \varepsilon_{i,t,h+2} + \beta_3 \varepsilon_{i,t,h+3} + \cdots,$$

where $\varepsilon_{i,t,h}$ denotes the news that becomes available between the time when horizon $h + 1$ forecast is made and the time when horizon h forecast is made.; and the β_s, $s \in \{0,1,2,3,\dots\}$ represents the usage of news $\varepsilon_{i,t,s}$. We can omit the horizon index h since for each target year, only one consensus forecast is available each month. Let $\boldsymbol{r}_t$ be a vector of forecast revisions for the seven countries in our sample made in month t. The interconnectedness of the economies in our sample and their business cycle co-movements can be represented using a time-varying parameter dynamic factor model. The standard dynamic factor model is a workhorse in the literature on international business cycles, such as in Kose *et al.* (2003). Our empirical work uses a version proposed in Del Negro and Otrok (2008) that extends the standard specification. The measurement equation is

$$\boldsymbol{r}_t = \boldsymbol{A} + \boldsymbol{B}_t \boldsymbol{f}_t + \boldsymbol{u}_t,$$

where

$$\boldsymbol{u}_t = \boldsymbol{\rho} \boldsymbol{u}_{t-1} + \boldsymbol{v}_t$$

and

$$\boldsymbol{f}_t = \boldsymbol{\phi}_1 \boldsymbol{f}_{t-1} + \boldsymbol{\phi}_2 \boldsymbol{f}_{t-2} + \boldsymbol{\nu}_t.$$

The constant $\boldsymbol{A}$, idiosyncratic AR coefficients $\boldsymbol{\rho}$, and factor AR coefficients $\boldsymbol{\phi}_1$ and $\boldsymbol{\phi}_2$ are time invariant parameters. As a standard practice, the components of $\boldsymbol{v}_t$ and $\boldsymbol{\nu}_t$ are normalized to follow the standard normal distribution so as to fix the scale of the factor loadings $\boldsymbol{B}_t$.

Since we have both developing economies and industrialized countries in our sample, we estimate two factors. To separately identify them, the factor loadings of the United States and Europe on the second factor is constrained to be zero. This results in a difference in the way the two factors are interpreted. The first factor, which all countries load on, is the world factor that captures shocks that are common to all the countries in the sample. The second factor, which only Asia countries load on, becomes an Asia factor.

One important assumption of the model is that the innovations $\boldsymbol{v}_t$ and $\boldsymbol{\nu}_t$ are independently and identically distributed across economies and over time. The implication of this assumption is that shocks to an economy are decomposed into two parts. One part originates from within the economy itself, and the other from the common factors. Unlike the work of Lahiri and Zhao (2017), our model does not explicitly allow the identification of shocks originated from a specific foreign economy. We believe this is a reasonable simplification. First, given the focus of this paper, we do not gain much more insights from being able to separately account for shocks originated from each foreign economy. Second, imposing this restriction on the common shocks results in more conservative estimates of

[8] The efficiency of the survey forecasts from Consensus Economics Inc. are also examined in Isiklar *et al.* (2006). Though using a much smaller sample, they come to conclusions similar to those in Lahiri and Zhao (2017).

the role of business cycle co-movements. So our results are less likely to overemphasize the importance of common shocks. Third, as an empirical matter, Lahiri and Zhao (2017) showed that shocks originated from specific foreign countries have little impact on an economy, provided that common international shocks have been accounted for.

Another feature of the model is that the factor loadings are allowed to be time-varying. This may be due to changes in bilateral trade relationships and policy shifts affecting the degree of financial market integration. These changes are known to be pronounced especially in Asia developing economies. Given this belief, changes in the factor loadings are more likely to be permanent.[9] Therefore, $\boldsymbol{B}_t$ is specified as a random walk without drift. This also makes our results less likely to be influenced by high frequency transitory shocks. Specifically, let

$$\boldsymbol{B}_t = \boldsymbol{B}_{t-1} + \boldsymbol{\eta}_t.$$

The elements of $\boldsymbol{\eta}_t$ are assumed to have country-specific but time-invariant variances and are independent across countries. This setup ensures that the factor loadings do not capture business cycle co-movements even though they are time-varying. Intuitively, the factors are interpreted as regional and global business cycles, and the factor loadings reflect economies' exposure to these common cycles. One may be concerned about the signs of the two factors, because the model stays the same even if we multiply both the factors and the loadings by -1. We do not have such a concern, because an incorrect sign would be immediately apparent when we examine the estimated factors during known recession periods.

The model is estimated using a Gibbs sampler according to the appendix of Del Negro and Otrok (2008) with 44000 draws (with first 4000 discarded). Following their practice, we use normal priors for constants with mean 0 and precision 0.01. The inverted gamma(1, 0.001) priors are used for idiosyncratic innovation variances. The priors for factor AR coefficients are normal with mean 0 and precision 1 and 1.33 respectively for the two factors. The priors for idiosyncratic AR coefficient is normal with mean 0 and precision 0.2. Finally, the priors for all factor loadings are normal with 0 mean and variance 20. We estimate the model using only the current year forecasts so as to form a continuous series of forecast revisions with no overlap and no gap in between. In our estimation sample, we have 12 forecast revisions for each target year, some of which derived using next-year forecasts when necessary.[10] Standard summary statistics of the estimation sample are reported in Table 1.

4. Empirical Results

4.1. Stylized facts about business cycle co-movements

A standard statistic that has long been used to measure business cycle synchronization is the simple correlation coefficient. Each pairwise correlation between two economies corresponds to the level of co-movement in their respective business cycles. By averaging all the pairwise correlations, we show concisely the overall degree of synchronization among all the economies. Figure 3 plots average pairwise correlations calculated using a

[9] See Del Negro and Otrok (2008) for a more detailed discussion of the choice between a random walk and a stationary process and references therein.

[10] Forecasts for India target fiscal years rather than calendar years, which are three months apart. As a result, we have to discard 3 out of 24 observations for each target year so as to align forecasts for India with the rest of the forecasts. This also means that some of the forecasts for India used in the sample are next-year forecasts. See Lahiri and Zhao (2017) for a more detailed explanation.

rolling window of 12 month for four sets of countries: all sixteen individual economies in our sample, the seven countries (groups) used to estimate the model, the four European countries; and the eleven economies in Asia. When interpreting these correlations, we need to keep in mind that they are not the between real GDP growth rates, but between forecast revisions. Therefore, when the forecasts are not fully efficient, there would be lags. But empirically the lags pose little problem: Since the correlations are calculated using a rolling window of past observations, there will always be lags by construction.

The most immediate observation from Figure 3 is that the average pairwise correlations evolve in largely the same pattern regardless of the set of countries involved. The cross-country correlations are stable on average, in that no apparent long-term trend is observed. However, significant spikes occur around crisis periods. Comparing the top right plot in Figure 3 with the static correlations in Table 2 for the same set of countries and country groups, we can see that the moderate levels of correlations observed over the entire sample period are driven almost exclusively by a few crisis periods.

4.2. The global and regional business cycles

Given the identifying restrictions imposed on the two common factors, we can interpret the first factor as representing the global business cycle, and the second as representing the regional business cycle in Asia. Estimates of the two factors are plotted in Figure 4. The solid line shows the median and the shaded area represents the 0.9 highest posterior density region. From the top plot showing the first factor, two episodes of recessions can be observed, both correspond to recessions in the United States. The first around 2001 to 2002; and the second from 2008 to 2009. This is hardly surprising given the important role the US economy plays on the global stage. The factor declined around 2009 much more that it did around 2001, consistent with the profound global impact of the 2008 crisis. As most other economies have significant exposures to this common factor, shocks to the US economy have a profound impact around the world. The second common factor is shown in the bottom plot. Representing the Asia regional business cycle, this factor dropped significantly during the period of the Asian financial crisis. It also declined notably around 2009 for obvious reasons. These movements are consistent with our interpretation of the two factors, and our intuitions on the global and regional economic cycles.

4.3. Measuring business cycle connectedness

Using our time-varying parameter dynamic factor model, we can measure the impact of the global and the regional business cycles. For each time period, we compute the contribution of a factor by multiplying its variance and loading then dividing the result by the variance of the dependent variable.[11] To account for possible inefficiencies in the forecasts, we report the average variance decompositions over rolling windows of one year. These statistics for the United States, Europe, China, and India are plotted (from top to bottom) in Figure 4. The vertical axis shows the fraction of variance attributable to each factor. Since the factor loadings of the United States and Europe on factor 2 are constrained to be zero, they do not show up in the figure.

For the United States, on average, the contribution of common shocks was about 15% before 2007. It increased to about 20 to 25% since the 2008 recession, before declining to

[11] Diebold and Yilmaz (2015) promote the use of modern network theory in measuring global business cycle connectedness. Their measures can be easily calculated using the variance decompositions we compute from our model. Specifically, their measure of total connectedness, in our context, is the sum of the contributions of the two factors.

the pre-recession level since around 2014. However, during the sample period, it fluctuated significantly, reaching as low as 7% and as high as 40%. For Europe, for the most part before the 2008 crisis, the contribution of the common shocks fluctuated around 30 to 40%. This number decreased sharply to only 20 percent during the crisis period and the immediate aftermath, before returning to its original level.

For China and India, the contributions of the common factors are smaller in general. Both factors together account for about 20 to 30% for China and about 10 to 20% for India. There are other differences between the two countries. For China, the two common factors often seem to substitute each other, while for India, the factors often behave as complements. Towards the end of the sample period, the contributions of the common factors slowly decline in the case of India while it is the opposite in the case of China. Overall, our empirical evidence seems to suggest no systematic changes in business cycle synchronization. While there are large fluctuations from time to time, they're more likely to be transitory changes rather than permanent structural shifts.

While the model does not explicitly identify shocks originated from specific foreign countries, our observations here correspond well with the results from the subsample analysis in Lahiri and Zhao (2017). In general, for industrialized countries like the United States and Europe, shocks that are important to the local economy are often international in nature, in the sense that variances and fluctuations observed in the industrialized countries are often observed around the world. While for developing economies, apart from being affected by shocks originated from the industrialized countries, shocks that are common to the developing economies and idiosyncratic shocks are also important contributors of business cycle fluctuations.

5. Conclusions

Extending our previous work on international transmission of economic shocks, this paper quantifies the impact of business cycle synchronization on industrialized countries and Asia developing economies using real GDP growth forecasts. Based on a Bayesian time-varying parameter dynamic factor model of forecast revisions, we report estimates of a global and a regional business cycle and the contributions of their fluctuations to individual economy's growth.

Our results highlight a significant amount of global spillovers of real economic shocks from industrialized countries, while a regional common business cycle in Asia appears as important as the global cycle. We find no evidence of permanent shifts in the degree of business cycle synchronization. Instead, transient shocks to business cycle co-movements played a dominant role in the last 20 years. Hopefully, our work would spark future research on this topic. With an expanded data set covering a longer period and more economies, one would be better positioned to identify the existence, magnitude, and length of potential permanent shifts in business cycle co-movements.

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Table 1: Summary Statistics of Forecast Revisions

Country	Mean	Std. Dev.	Min.	Max.
USA	0.0022	0.191	-0.731	0.626
Europe	-0.0257	0.117	-0.813	0.411
Japan	-0.0156	0.333	-2.039	1.129
India	-0.0164	0.200	-0.680	1.370
China	0.0196	0.152	-0.603	0.735
S.E. Asia	-0.0406	0.343	-3.303	1.015
N.E. Asia	-0.0227	0.314	-1.992	0.997

Table 2: Correlations between Forecast Revisions

Correlations	USA	Europe	Japan	India	China	S.E. Asia
Europe	0.202					
Japan	0.241	0.325				
India	0.141	0.109	0.226			
China	0.052	0.145	0.226	0.214		
S.E. Asia	0.117	0.278	0.382	0.283	0.386	
N.E. Asia	0.313	0.472	0.503	0.308	0.346	0.661

Figure 1: Forecasts of Real GDP Growth: United States 1996 to 2017

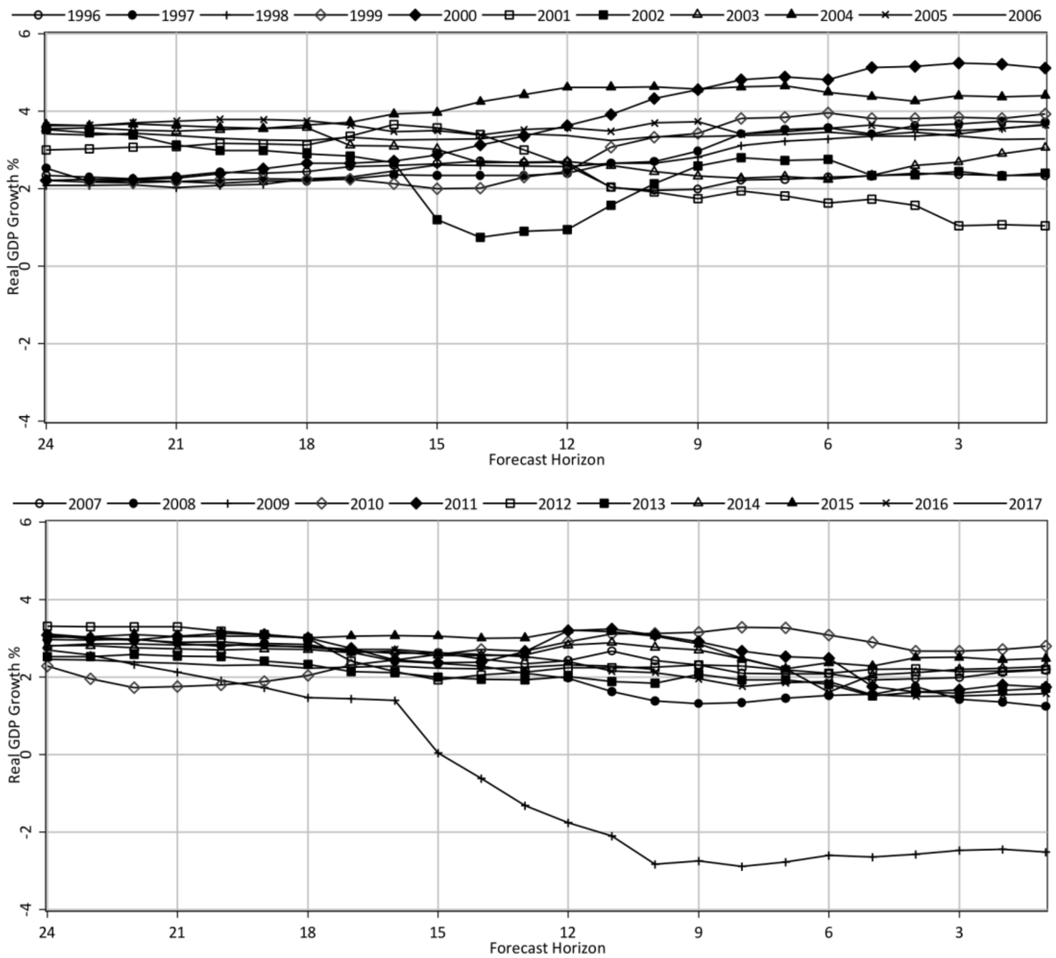
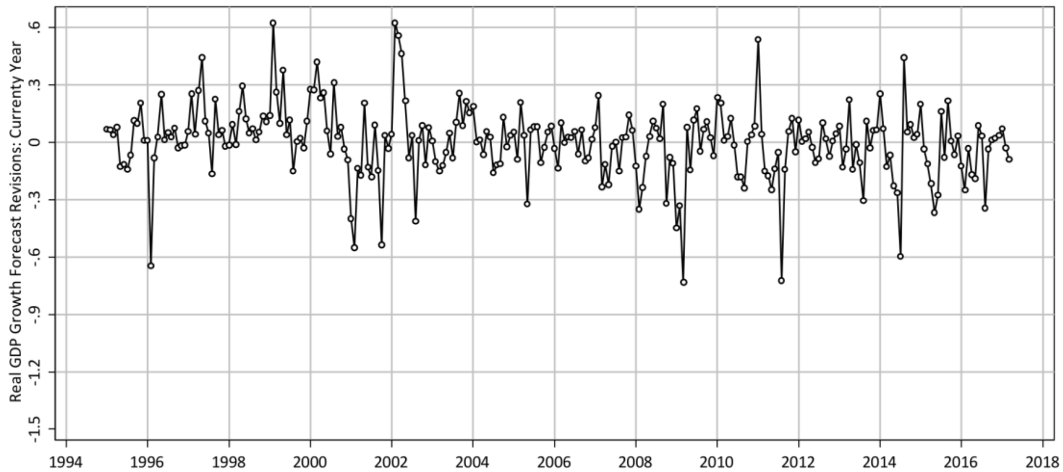


Figure 2: Forecast Revisions of United States Real GDP Growth: 1996 to 2017

Revisions of Current-Year Forecasts



Revisions of Next-Year Forecasts

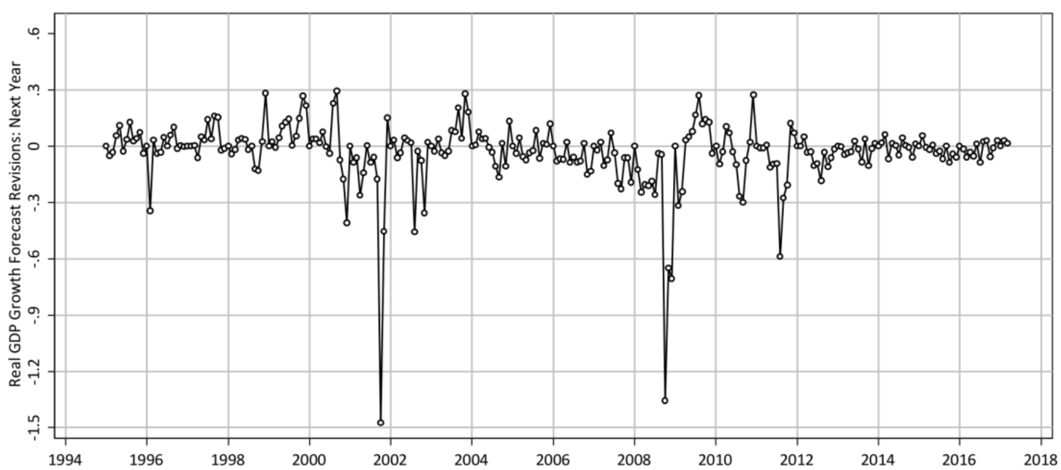


Figure 3: Average Pairwise Correlations: Rolling Window of 12 Months

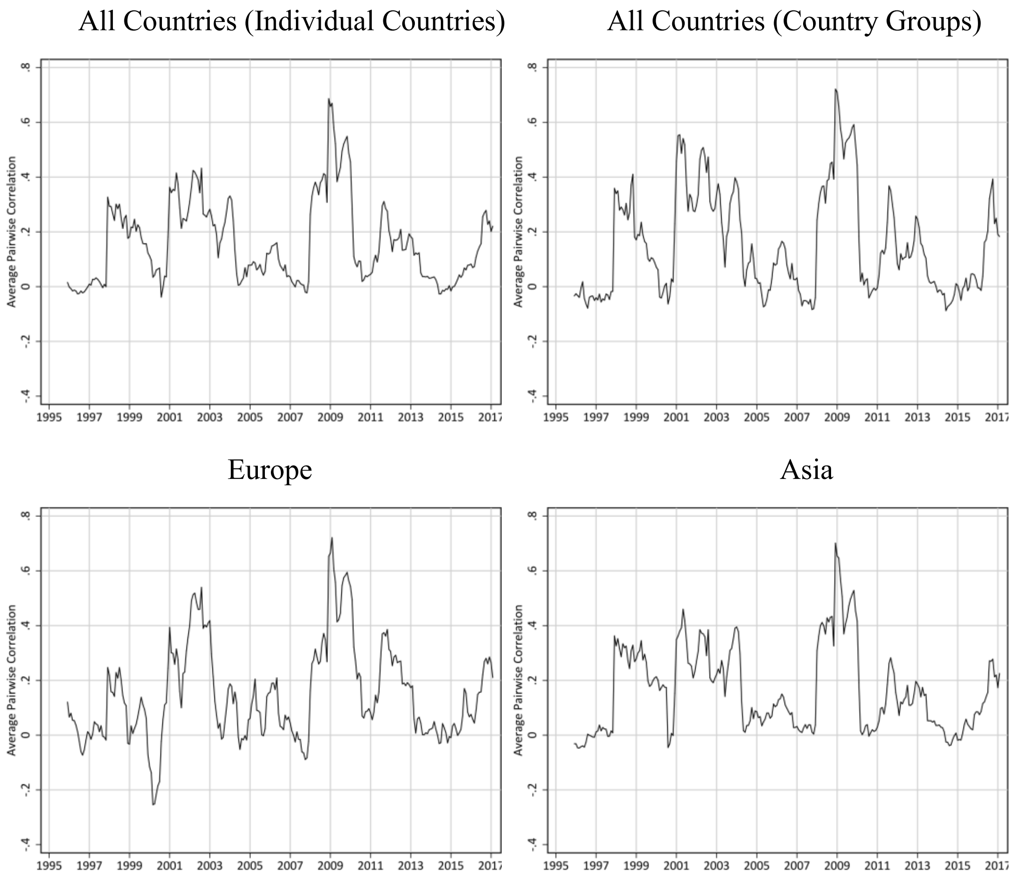
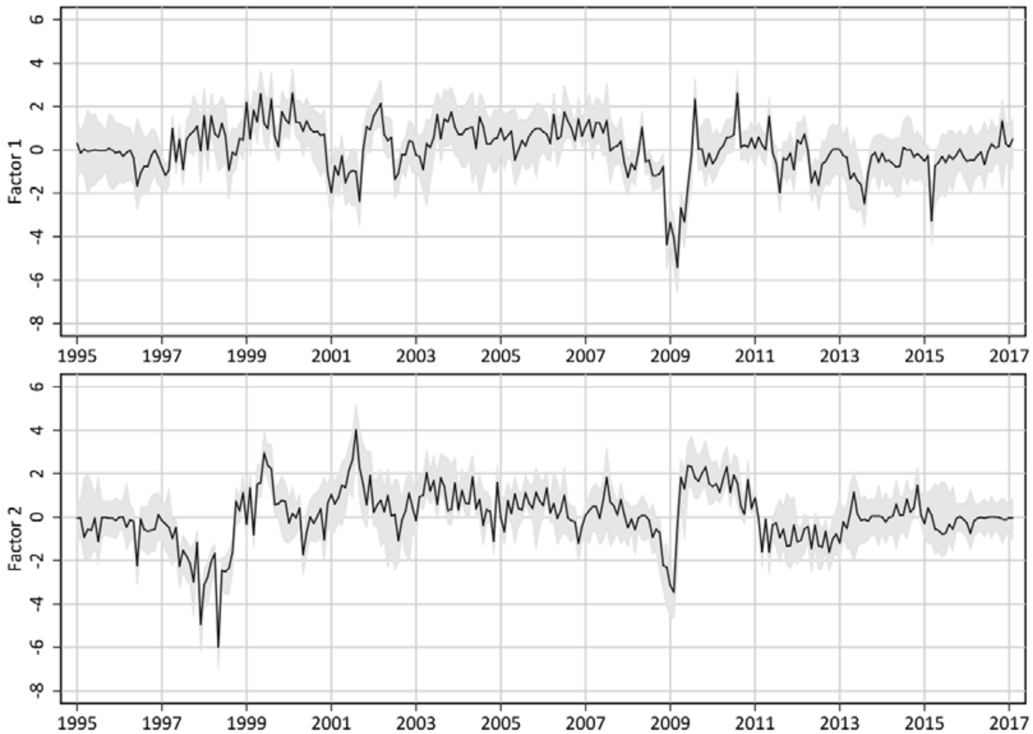
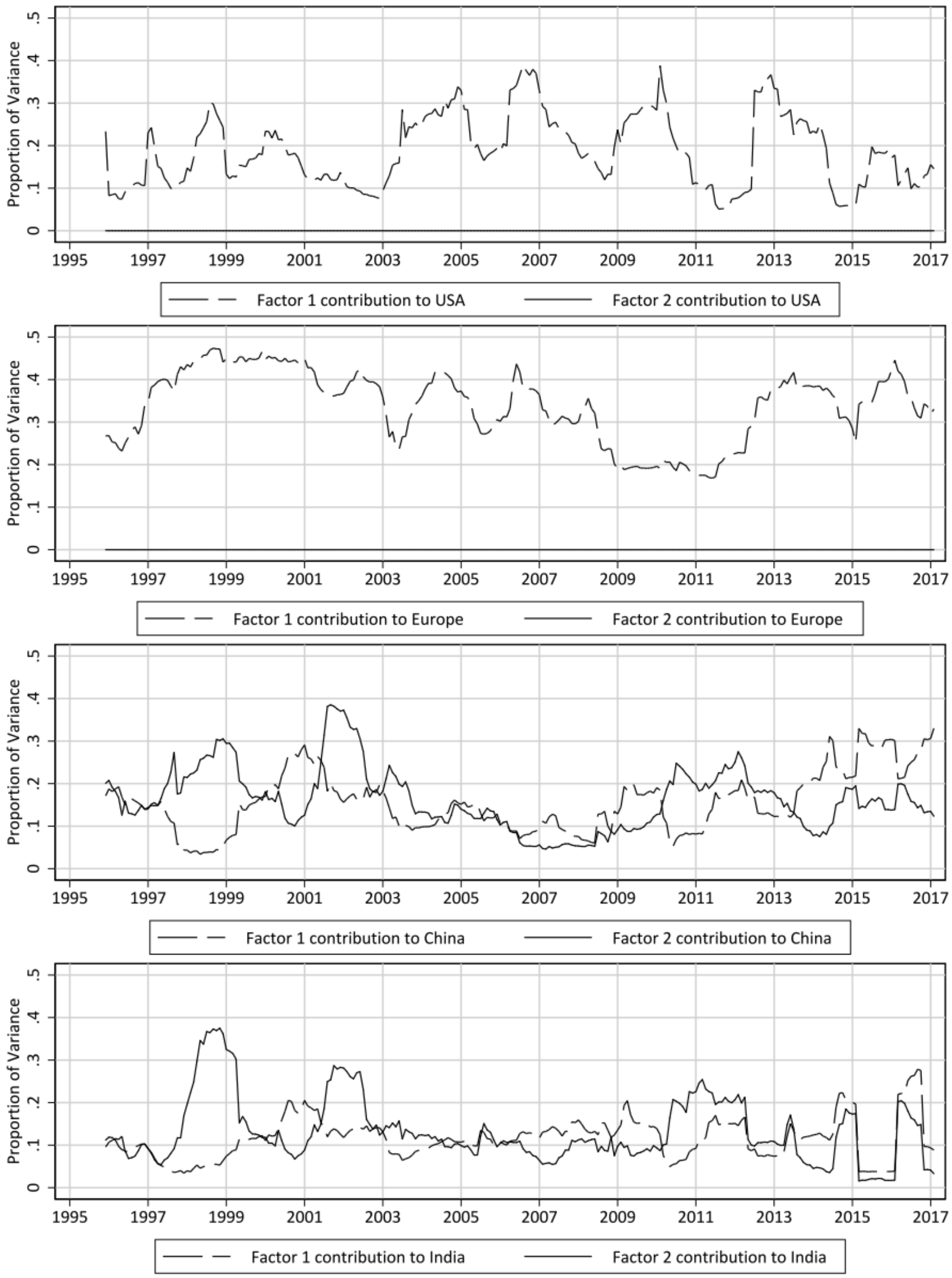


Figure 4: Estimated Factors from the Bayesian Time Varying Parameter Model



Median+/- 90% band

Figure 5: Variance Decompositions from the Bayesian Time Varying Parameter Model: USA, Europe, China, and India



Factor 1's contribution to USA and Japan is zero by construction.