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The Effects of Global and Regional Shocks on Asian Business Cycle Synchronization

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Abstract

This paper studies the evolution of the degree of Asian business cycle synchronization and assesses the impact of global and regional shocks on output interdependence across Asia since the 1990s. We employ a dynamic factor model to decompose output fluctuations into a global factor common to all countries in our sample, regional factors that capture any remaining common fluctuations across countries within each region, and an idiosyncratic component that captures country-specific characteristics. In particular, we categorize the 19 countries in our sample into four groups -- non-Asia, East Asia, South Asia and Southeast Asia, thereby accounting for heterogeneous dynamics of sub-regional co-movement. Results show that, over the past two decades, global shocks and regional shocks are playing a critical role in determining Asian output synchronization. As the process of globalization has picked up, both shocks increasingly explain the co-movement of output, which leads to a higher degree of business cycle synchronicity across Asia.

JEL Classifications: C11, E3

Keywords: Bayesian estimation; business cycle; dynamic factor; Markov Chain Monte Carlo (MCMC); shocks; co-movement

1. Introduction

Over the past two decades, given the rapid increase in trade and financial linkages in Asia, we have seen a greater openness to trade and financial flows which has made Asian economies more interdependent on each other. However, theories have ambiguous predictions on the impact of rising trade and financial interdependencies. On the one hand, an increase in trade will generate the

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spillover of shocks across countries, resulting in more highly correlated output fluctuations. For example, when the demand for smart phones goes up, economies that produce electronic components will profit, thereby boosting growth across economies. On the other hand, if stronger trade linkages generate an increased specialization of production on comparative advantages across countries, and if, the sector-specific shocks are dominant, then, the degree of co-movement of output may fall. Likewise, rising financial linkages create greater spillover effects, which, simultaneously, maybe offset by increased financial specializations and greater exposure to varied sector-specific shocks (Cetorelli & Goldberg, 2012; Kalemli-Ozcan, Papaioannou, & Perri, 2013). Therefore, the degree of evolution of the business cycle synchronization in Asia ultimately remains an empirical issue.

Such an issue is also of policy relevance. The 1997 Asian financial crisis and the most recent European sovereign-debt crisis pose challenges along with benefits in introducing a common currency in Asia. One of the criteria to enter an optimal currency area (OCA) (Mundell, 1961) is that countries with positively correlated business cycles are more likely to join an OCA, ceteris paribus. A single currency union foregoes monetary independence in pursuit of the benefits from a common policy, such as a reduction in the transaction costs associated with trading goods and services between economies with different currencies. Thus, a study of output synchronization among Asian countries is expected to shed some light on the desirability of a regional currency union.

A number of approaches have been adopted in existent literature to examine the degree of synchronization between macroeconomic variables. The most basic and widely-used methodology is a correlation analysis (Baxter & Stockman, 1989; Bordo & Helbling, 2003), which calculates the bivariate correlation among economic variables. Another alternative measure of synchronization is the concordance index (Harding & Pagan, 2006), which assesses the synchronization of business cycle turning points across countries. However, two main drawbacks are associated with these measures: firstly, such static measures fail to take into account any dynamic properties of the data, such as autocorrelations. Secondly, they do not separate common shocks from idiosyncratic shocks, and are therefore, unable to study the impact of common shocks on business cycle synchronization.

However, dynamic factor models overcome these problems. A number of recent studies (Gregory & Head, 1999; Kose, Otrok, & Whiteman, 2003, 2008; Bernanke & Boivin, 2003; Bernanke, Boivin, & Eliasz, 2005; Stock & Watson, 2005; Belviso & Milani, 2006) have utilized dynamic factor models to capture the co-movement and linkages among macro variables. The intuition is that information contained in very large data sets of economic variables can be characterized by a relatively small group of latent factors. Extracting such factors can offer us more information on the business-cycle behavior and benefit future policy analysis.

Due to its desirable feature, dynamic factor models are widely used in constructing economic indicators (Burns & Mitchell, 1946; Sargent & Sims, 1977; Geweke, 1977) and characterizing and monitoring regional, country-specific and global business cycles (Gregory & Head, 1999; Kose *et al*., 2003, 2008). Factor models have also provided a useful analytical framework for forecasting with many macroeconomic predictors (Koop & Potter, 2004; Stock & Watson, 2002, 2005). Chauvet (1998) and Chauvet and Hamilton (2006) use dynamic factor models with regime switching to examine business cycle turning points and compute recession probabilities. Additionally, factor models are broadly applied in finance and exchange rate analysis (Geweke & Zhou, 1996; Kim, Shephard, & Chib, 1998; Aguilar & West, 2000; Chib, Nardari, & Shephard, 2006).

Motivated by the aforementioned considerations, we employ a dynamic factor to study the dynamic co-movement of output growth across Asia and to disentangle the effects of global and regional shocks on business cycle synchronization. In particular, we estimate a dynamic factor common to all countries in our sample, four regional factors that capture any remaining common fluctuations across countries within each region, and an idiosyncratic component that captures country-specific characteristics, and use the former two types of factors to trace business cycle fluctuation sources. We apply an annual output growth dataset on 19 countries over the period between 1990 and 2011 given the process of globalization picked up pace in the past two decades. Unlike previous studies, which only consider Asia as a whole, we divide Asia into three sub-regions: East Asia, South Asia and Southeast Asia. Such geographic divisions of Asia account for the common shocks shared across countries within the sub-region, thereby, capturing heterogeneous dynamics of sub-regional co-movement.

Simulation-based estimation, using recently developed Markov Chain Monte Carlo (MCMC) algorithms, allows us to better handle large systems than traditional maximum likelihood approach. We also conduct analysis on variance decomposition as well as correlation between output growth and common factors to clarify the role of each factor in driving output co-movement.

The remainder of the paper is organized as follows. In Section 2, we formalize the econometric model and estimation methodology, while Section 3 presents our main results. Section 4 offers concluding remarks.

2. Methodology

2.1. Model Specification

We apply a dynamic model to analyze annual real GDP growth for 19 countries. The sample includes five non-Asian industrial countries, five East Asian countries, four South Asian countries, and five Southeast Asian countries over the period 1990-2011. Industrial countries are composed of United States, Germany, Canada, France, and United Kingdom. Asian economies include China, Taiwan, Hong Kong, Japan, Korea, India, Bangladesh, Pakistan, Sri Lanka, Malaysia, Indonesia, Philippines, Singapore and Thailand. We use the log difference GDP data to render stationarity and remove the mean from each series. Data Appendix shows the distribution of countries among four groups.

We construct a dynamic factor model to decompose output growth into a country-specific autoregressive component, a world factor, a regional factor and an idiosyncratic component. These factors capture common fluctuations across all countries as well as across a specific region. Particularly, a world factor is common to the entire dataset and a regional factor is common to a subgroup of countries.

For country i, which belongs to group k, its output growth at time t, y_{it}, is modeled as follows:

$$y_{it} = \beta_i y_{it-1} + a_i^g g_t + a_i^k f_t^k + \varepsilon_{it},$$

$$E\left(\varepsilon_{it}\varepsilon_{j,t-s}\right) = 0, for\ i \neq j, and\ s \neq 0,$$

$$E(\varepsilon_{it}\varepsilon_{it}) = \omega_i,$$

where g_t is the global factor that captures the worldwide co-movement in output growth, f_t^k is the factor specific to region k that only affects countries in that region and ω_{it} is the country-specific cyclical movement. The impact of latent factors is not homogeneous to all countries. This is captured by the country-specific coefficients or factor loadings, a_i^g, a_i^k, which measure country i's heterogeneous response to the latent common factors. Stack observations over i, we can rewrite the model as:

$$y_t = By_{t-1} + AF_t + \varepsilon_t \text{ ,} \tag{1}$$

$$\varepsilon_t \sim N(0, \Omega),$$

where $B = diag(\beta_1, . . ., \beta_N)$ and $\Omega = diag(\omega_1, . . ., \omega_n)$. $diag$ returns a matrix with vector elements on its main diagonal. We use the following autoregressive process to model the dynamics of the factors:

$$F_t = \Gamma F_{t-1} + \nu_t, \tag{2}$$

$$\nu_t \sim N(0, \Sigma),$$

where $\Sigma = diag(\sigma_1^2, \dots, \sigma_k^2)$ and K is the number of latent factors. The lag polynomials can be of different order; however, increasing to order of two does not make a qualitative difference to the findings. Thus, for simplicity, we impose AR (1) in our system.

This linear state-space model can be written as follows:

$$Y_t = X_t\beta + AF_t + \varepsilon_t,$$

$$F_t = \Gamma F_{t-1} + \nu_t$$

The Γ matrix is diagonal and the A matrix of factor loadings or sensitivities measures the instantaneous impact of the common factors on each series Y_t.

One of the advantages of the chosen specification is that it is fairly flexible and allows for distinguishing between global shocks and regional shocks, which may also give rise to co-movement among countries.

Because neither the factor F_t nor the loadings vector A is known, for identification reasons we restrict one of the factor loadings to be unity 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. The model is capable of reproducing complex dynamic behavior because intertemporal cross-correlations can be captured through the unobserved factor as well as lags of the dependent variable vector.

2.2. Estimation Approach

The estimation approach we adopt for our dynamic factor model is Bayesian. The model is estimated efficiently by the Markov Chain Monte Carlo (MCMC) sampler for state space models developed in Chan and Jeliazkov (2009). This algorithm technique makes it possible to generate random samples of the desired posterior distribution of the parameters and factors, thus enabling us to draw subsequent inferences. Algorithm details are provided in the appendix. The MCMC sampler proceeds in the following steps.

Sampling scheme: MCMC sampling of the dynamic factor model

1. Sample $[\beta | y,\ A,\ \Omega,\ \gamma, \sigma^2]$
2. Sample $[A, F | y,\ \beta,\ \Omega,\ \gamma, \sigma^2]$ in one block as follows
    a. Sample $[A | y,\ \beta,\ \Omega,\ \gamma, \sigma^2]$ marginally of F
    b. Sample $[F | y,\ \beta,\ A,\ \Omega,\ \gamma, \sigma^2]$
3. Sample $[\Omega | y,\ \beta,\ A,\ F]$
4. Sample $[\gamma | F,\ \sigma^2]$
5. Sample $[\ \sigma^2 | f,\ \gamma]$

These steps are iterated 11,000 times, of which the first 1, 000 draws are discarded as bum-ins to remove the effect of the starting values of the chain. It is important to note that because this algorithm produces draws from the joint posterior distribution of all model unknowns, subsequent inferences based on the simulated factors fully account for all parameter uncertainty (unlike plug-in approaches). Moreover, the framework is quite flexible and can easily accommodate systems with variable-specific lag lengths, more complex factor dynamics, or many macroeconomic predictors (Stock & Watson, 2002).

3. Results

3.1. Global and Regional Factors

Figure 1. Estimated global factor over the period 1990-2011

The estimated posterior mean of the global factor from 1990 to 2011 is shown in Figure 1. It reveals that the factor captures the timing of worldwide recessions and expansions quite well, and that it also gives an idea of the relative severity and dynamic evolution of each recession. The key finding from this figure is that the latest global crisis that started in 2007, and plummets deeply around 2009, appears to be the worst since 1990s. In addition, major economic events in the past two decades are well described through the factors: the recession in early 1990s and the recovery in the late 1990s; the collapse of the internet bubble in early 2000s and the subsequent recovery.

Once we account for global factors, which pick up common fluctuations across all countries, the regional factors capture any remaining co-movement among countries within each region. The regional factors for East Asia and Southeast Asia are depicted in Figure 2 and Figure 3, respectively. The East and Southeast Asian factors suggest that most economies in these regions experienced three major downturns in the last two decades: the 1997-1998 Asian crisis, a less pronounced downturn starting in the early 2000s, and the most recent Global crisis starting on December 2007. Also note that the Asian financial crisis of 1997-1998 is prominent both in the East Asian factor and the Southeast Asian factor, well in line with the fact that handful Asian countries were directly affected by the crisis.

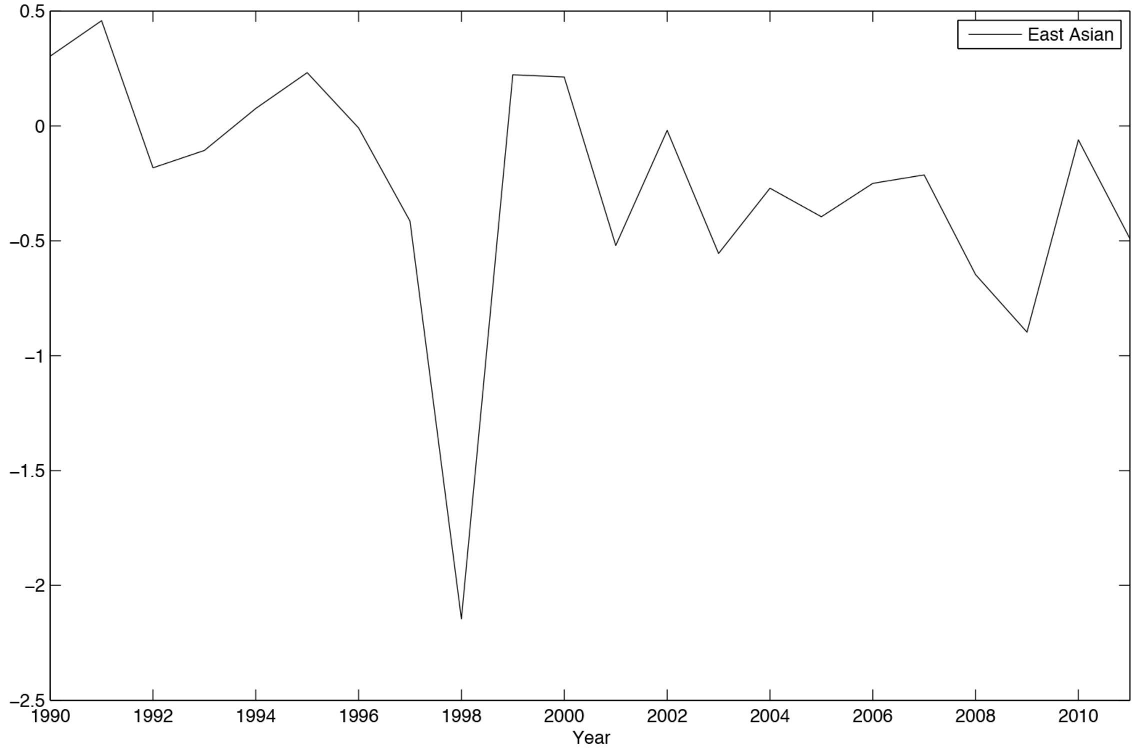

Figure 2. Estimated East Asian factor over the period 1990-2011

Figure 3. Estimated Southeast Asian factor over the period 1990-2011

The estimated South Asian factor suggests a quite different growth dynamics (Figure 4). The recession in early 1990s and the recession in early 2000s are well documented through the factor. The regional recovery, following the early 2000s downturn, is strikingly prominent, reflecting strong economic growth enjoyed by South Asian countries. The most recent crisis, however, slows down the regional economic growth significantly, though its impact is not massive enough to bring South Asia to a recession.

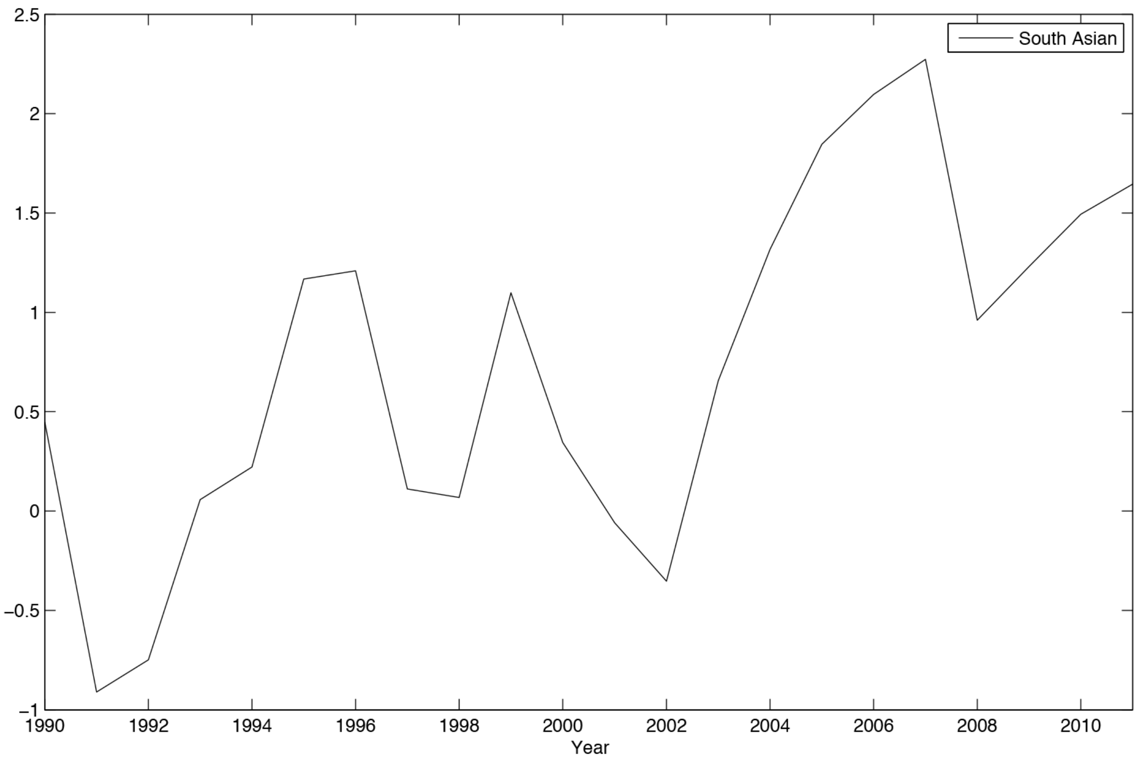

Figure 4. Estimated South Asian factor over the period 1990-2011

The estimated global factor loadings are reported in Table 1, along with the standard deviation. The factor loadings measure the sensitivity of output growth to common factors. If one country is positively affected by a shock and the other is negatively affected by the same shock, the model will assign a positive loading to one country and a negative loading to the other. Therefore, two countries with same-sign factor loadings suggest that the common factor affect both countries in the same direction. In addition, similar magnitude of factors represents similar closeness or responsiveness to the factor. For example, China, with a small positive value of 0.05, indicates its sufficiently different growth dynamics.

From the rest of the region, Economies such as Hong Kong and Taiwan, with similar regional factor loadings of 0.95 and 1, suggest almost identical responsiveness to the regional factor. In Southeast Asia, Malaysia, Indonesia and Thailand with factor loadings at 1, 1.03, and 0.9 respectively, implying similar sensitivity to regional shocks. On the other hand, South Asian countries present very diverse responses to regional shocks, with negative factor loading for Pakistan and positive loadings for the rest of the region.

3.2. Measures of Synchronization

To understand the degree of co-movement in output growth among Asian countries and the associated driving forces, we present two different measures of synchronization. One is the share of output fluctuations explained by the dynamics of global factor as well as regional factor. The other measure is given by the simple correlation between the output growth and the common factor. The former approach is more desirable because it considers the entire dynamic processes of the common factors, whereas the latter approach, ignoring such dynamics, is easier to calculate for sub-samples, which makes evolution of the output co-movement on the regional and global level readily available.

Table 1. Factor loadings, full sample from 1990 to 2011

	Global	Non-Asian	East Asian	South Asian	Southeast Asian
United States	1	-0.22 (0.33)	0	0	0
Germany	1.27 (0.6)	1	0	0	0
Canada	1.04 (0.32)	-0.24 (0.37)	0	0	0
France	0.94 (0.36)	0.24 (0.31)	0	0	0
United Kingdom	1.06 (0.36)	-0.1 (0.39)	0	0	0
Taiwan	0.83 (0.5)	0	1	0	0
China	0.03 (0.25)	0	0.05 (0.29)	0	0
Hong Kong	0.46 (0.49)	0	0.95 (0.39)	0	0
Japan	0.58(0.41)	0	0.61 (0.36)	0	0
Republic of Korea	0.04 (0.65)	0	1.78 (0.43)	0	0
India	0.28 (0.64)	0	0	1	0
Bangladesh	0.00 (0.32)	0	0	0.2 (0.24)	0
Pakistan	0.24 (0.42)	0	0	-0.06 (0.35)	0
Sri Lanka	0.52 (0.52)	0	0	0.48 (0.38)	0
Malaysia	0.51 (0.53)	0	0	0	1
Indonesia	-0.14(0.53)	0	0	0	1.03 (0.24)
Philippines	0.59 (0.38)	0	0	0	0.35 (0.27)
Singapore	0.9 (0.43)	0	0	0	0.58 (0.26)
Thailand	0.43 (0.52)	0	0	0	0.9 (0.31)

3.2.1. Variance Decomposition

In order to calculate the relative contributions to its output growth fluctuations by different factors for each country, note that the growth rate of country i can be represented as follows:

$$y_{it} = \beta_i y_{it-1} + a_i^g g_t + a_i^k f_t^k + \varepsilon_{it} \tag{3}$$

Therefore,

$$var(y_{it}) = (\beta_i)^2 var(y_{it-1}) + \left(a_i^g\right)^2 var(g_t) + \left(a_i^k\right)^2 var\left(f_t^k\right) + var(\varepsilon_{it}) \tag{4}$$

The contribution of global factor to country i's output growth volatility is given by

$$\frac{\left(a_i^g\right)^2 var(g_t)}{var(y_{it})} \tag{5}$$

The contribution of regional factor k to country i's output growth volatility is given by

$$\frac{\left(a_i^k\right)^2 var(f_t^k)}{var(y_{it})} \tag{6}$$

The resulting variance decomposition of each country's output growth is reported in Table 2. On average, global factor accounts for 30% of output fluctuations across countries. Global factor is extremely important in explaining output fluctuations in non-Asian group, with global share of output variance amounted to 50%. Across Asian groups, Southeast Asia has the biggest global share of output variance, at 30%, where East Asia has the least, at 17%. In particular, for countries including China, Korea, India, Bangladesh, and Indonesia, global factor plays little role in explaining output fluctuations. Regional factor, on average, captures 38% of output growth volatility. Specifically, regional factor exerts a huge impact on East Asia and Southeast Asia, with a regional share of output growth volatility at 52% and 53%, respectively. Malaysia, Indonesia and Thailand, with similar regional shares of output fluctuations, suggest a higher degree of synchronization among each other. Philippines, on the other hand, is least influenced by common regional factor. China, Japan, India and Pakistan are not very sensitive to common factors as well. In China, global and regional factors combined account for only 9% of its output fluctuations, suggesting a different growth pattern than the rest of the region.

Table 2. Variance decomposition, full sample from 1990 to 2011

	Global factor	Regional factor
Non-Asian		
United States	0.69	0.03
Germany	0.26	0.17
Canada	0.56	0.03
France	0.39	0.03
United Kingdom	0.60	0.01
East Asian		
Taiwan	0.38	0.56
China	0.03	0.06
Hong Kong	0.15	0.66
Japan	0.30	0.34
Republic of Korea	0.05	0.89
South Asian		
India	0.04	0.49
Bangladesh	0.01	0.69
Pakistan	0.35	0.02
Sri Lanka	0.46	0.41
Southeast Asian		
Malaysia	0.18	0.69
Indonesia	0.01	0.82
Philippines	0.47	0.16
Singapore	0.66	0.27
Thailand	0.17	0.71
Average		
Global	0.30	0.38
Non-Asian group	0.50	0.05
East Asian group	0.17	0.52
South Asian group	0.21	0.41
Southeast Asian group	0.30	0.53

Table 3 shows the variance decomposition in a similar manner to Table 2 but based on models estimated separately for the two periods, 1990-1999 and 2000-2011. Across groups, evident is the substantial increase in the global share of output variation, from 25% to 40%. This indicates an increasingly stronger global business cycle in the past two decades. Although on average global shocks show an increasing impact on Asian countries, some outliers are still worth examining. China, India and Philippines are becoming more de-linked with the global shocks. In particular, India and China's output cycles are more attributable to domestic shocks and more resilient to adverse external shocks. On the other hand, the share of output fluctuations explained by regional factors drops down from 54% to 23%. Nearly every Asian group's output variation attributable to regional shocks decreases over the two periods, suggesting a weakening co-movement within Asia once we account for the global factor. However, note that countries tend to move closely with each other during crisis. The 1997-1998 Asian financial crisis is the main driving force behind the output co-movement in the 1990s, leading to a higher share of output variance explained by regional shock, whereas 2007-2008 global crisis accounts for the rise in the importance of global shock during the 2000s. Therefore, the presented results from variance decomposition are largely crisis-driven.

Table 3. Variance decomposition over two periods, 1990-1999 and 2000-2011

	1990-1999		2000-2011	
	Global factor	Regional factor	Global factor	Regional factor
Non-Asian				
United States	0.02	0.01	0.70	0.02
Germany	0.51	0.33	0.37	0.27
Canada	0.89	0.09	0.66	0.04
France	0.14	0.81	0.41	0.08
United Kingdom	0.88	0.01	0.51	0.07
East Asian				
Taiwan	0.02	0.90	0.50	0.32
China	0.22	0.01	0.07	0.01
Hong Kong	0.05	0.70	0.75	0.10
Japan	0.01	0.15	0.71	0.01
Republic of Korea	0.01	0.99	0.19	0.33
South Asian				
India	0.28	0.48	0.04	0.46
Bangladesh	0.01	0.88	0.04	0.25
Pakistan	0.01	0.88	0.62	0.01
Sri Lanka	0.03	0.93	0.53	0.39
Southeast Asian				
Malaysia	0.08	0.80	0.38	0.60
Indonesia	0.09	0.74	0.13	0.74
Philippines	0.39	0.14	0.19	0.15
Singapore	0.09	0.74	0.82	0.17
Thailand	0.25	0.68	0.35	0.34
Average				
Global	0.25	0.54	0.40	0.23
Non-Asian group	0.68	0.25	0.49	0.16
East Asian group	0.05	0.55	0.35	0.16
South Asian group	0.08	0.79	0.39	0.31
Southeast Asian group	0.18	0.62	0.37	0.35

3.2.2. Correlations between Output Growth and Factors

In order to better understand the evolution of co-movement in the last two decades, we calculate a 5-year rolling window correlation between output growth and the common factors. Figure 5 shows the average of this correlation between output and the global factor in regards to five different groups -- All, non-Asia, East Asia, South Asia and Southeast Asia. Asian groups share very similar pattern: a low correlation phase from 1994 to 2002 followed by a high correlation phase thereafter. The non-Asian countries, composed of industrial economies, show a consistently strong tie with the global factor till 2003, weakening down slightly around 2005 and gradually rising up to a new high level due to the most recent global crisis. The "All" line stands for the average correlation between output and global factor across all countries in our sample. A pronounced upward trend exists, as the degree of this correlation in the second decade is much higher than that in the first decade. Although the 2008-2009 crisis as well as the internet bubble burst of 2000-2001 explain most of the high correlation in the last decade, they cannot account for the high correlation during the non-crisis period (2003-2006). Particularly, from 2003 to 2006 Southeast Asia is more synchronized in response to global shocks than any other regional groups.

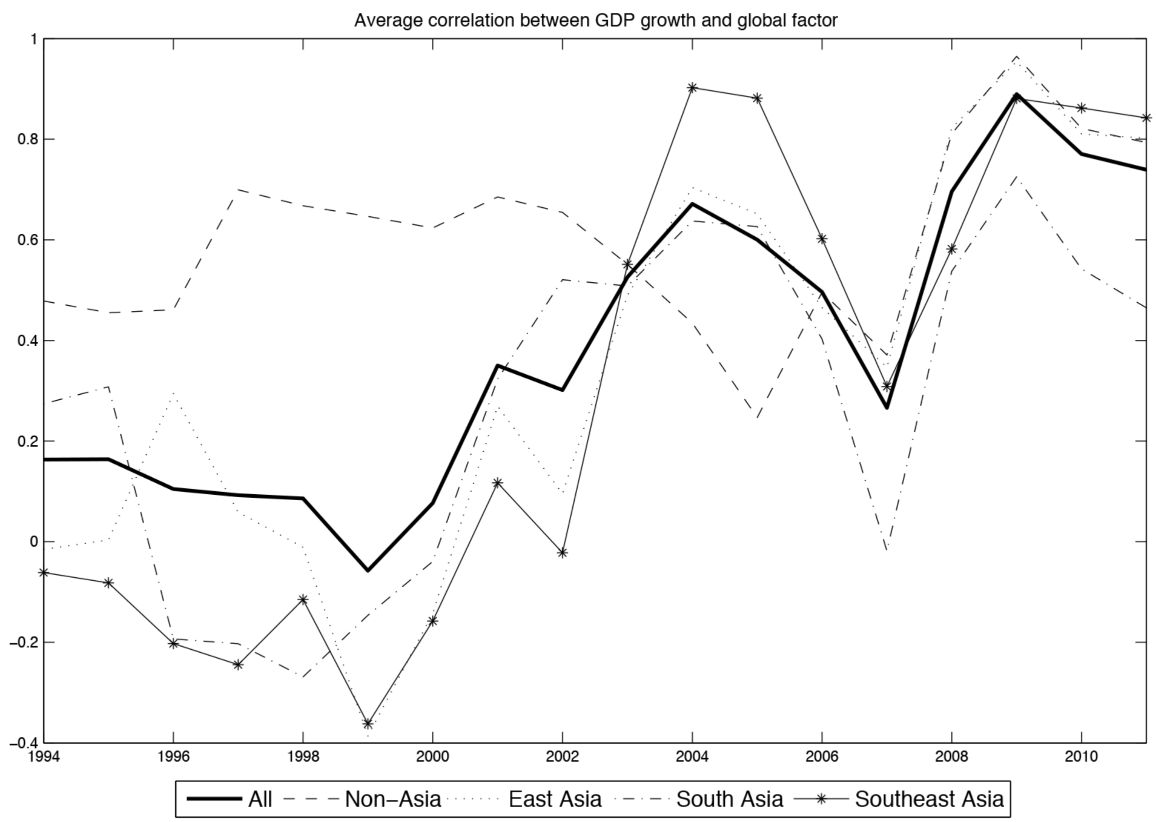

Figure 5. Average correlation between GDP growth and global factor for all groups

Moreover, previous studies documented the strong co-movement among the Newly Industrialized Economies (NIEs), namely, Singapore, Hong Kong, Taiwan and Republic of Korea. To examine such findings, we calculate the average correlation between NIEs' output and the global factor, and plot it in Figure 6 together with correlations for East Asia and Southeast Asia. NIEs experienced a much higher correlation with the global factor than the other two groups, except for the period 2004-2006, in which NIEs' degree of co-movement falls below the Southeast Asian group. In other words, NIEs synchronize strongly as a whole due to their high degree of linkages to global events.

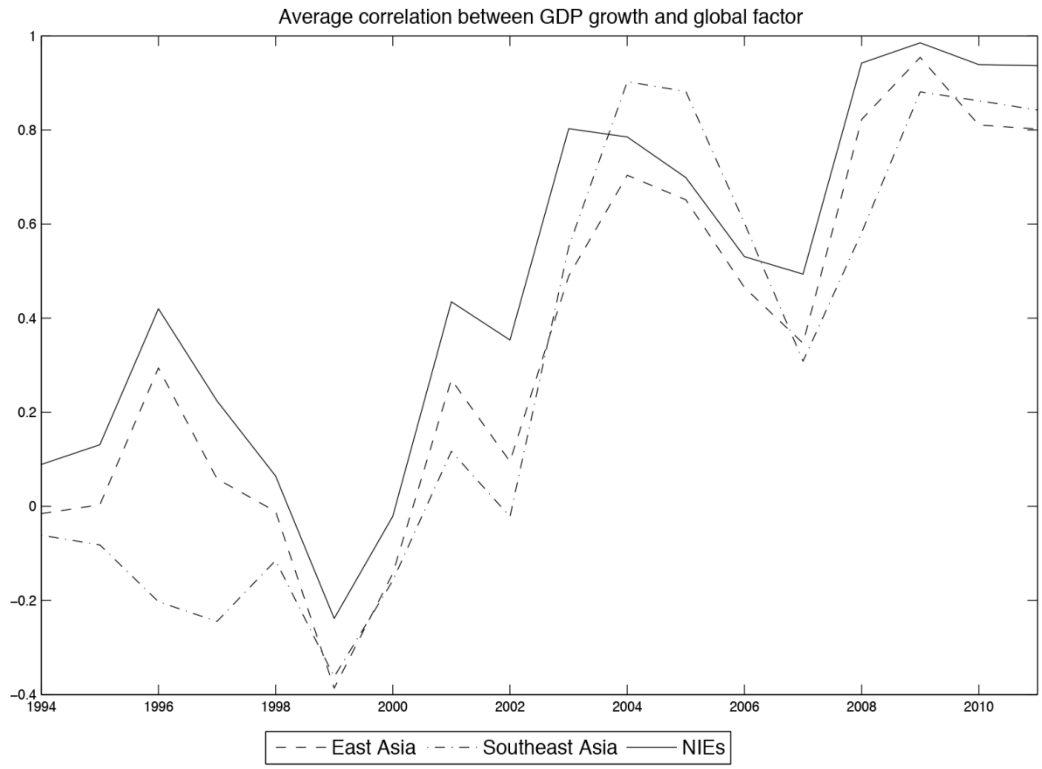

Figure 6. Average correlation between GDP growth and global factor for EA, SEA and NIEs

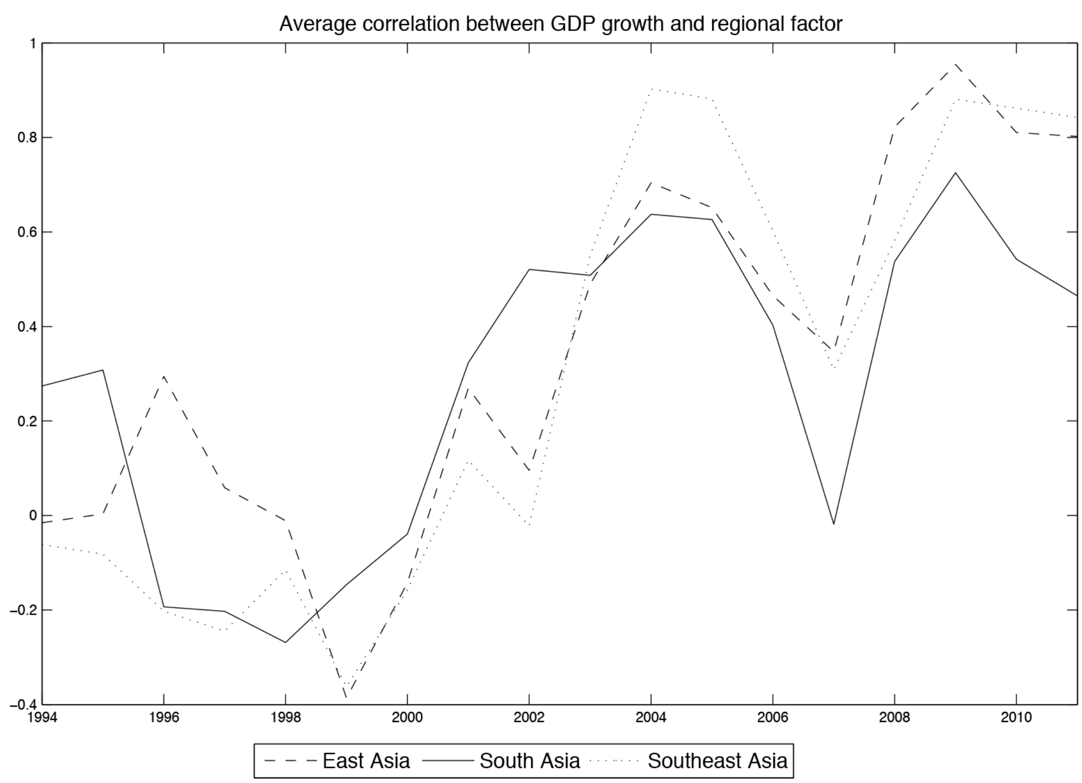

Figure 7. Average correlation between GDP growth and regional factor for EA, SA and SEA

Now we turn to the discussion of correlations between output growth and regional shocks. Figure 7 depicts the calculated 5-year rolling window correlation within East Asia, South Asia and Southeast Asia. South Asia, for example, experienced two distinct phases: the low correlation till 2003 and the subsequent high correlation. The average correlation for East Asia and for Southeast Asia has been very similar up to 2003, with a noticeable divergence evident thereafter. From 2003 to 2005, while the average correlation for Southeast Asia remains high (though drops at first), the correlation for East Asia declines markedly. Since 2005 onward, the correlation falls initially, bounces back accompanied by the onset of the recent global recession, and remains high thereafter. Figure 8 shows the average correlation between regional factor and output growth across countries. The rising trend suggests an increasing interdependence within each Asian group via the exposure to regional shocks.

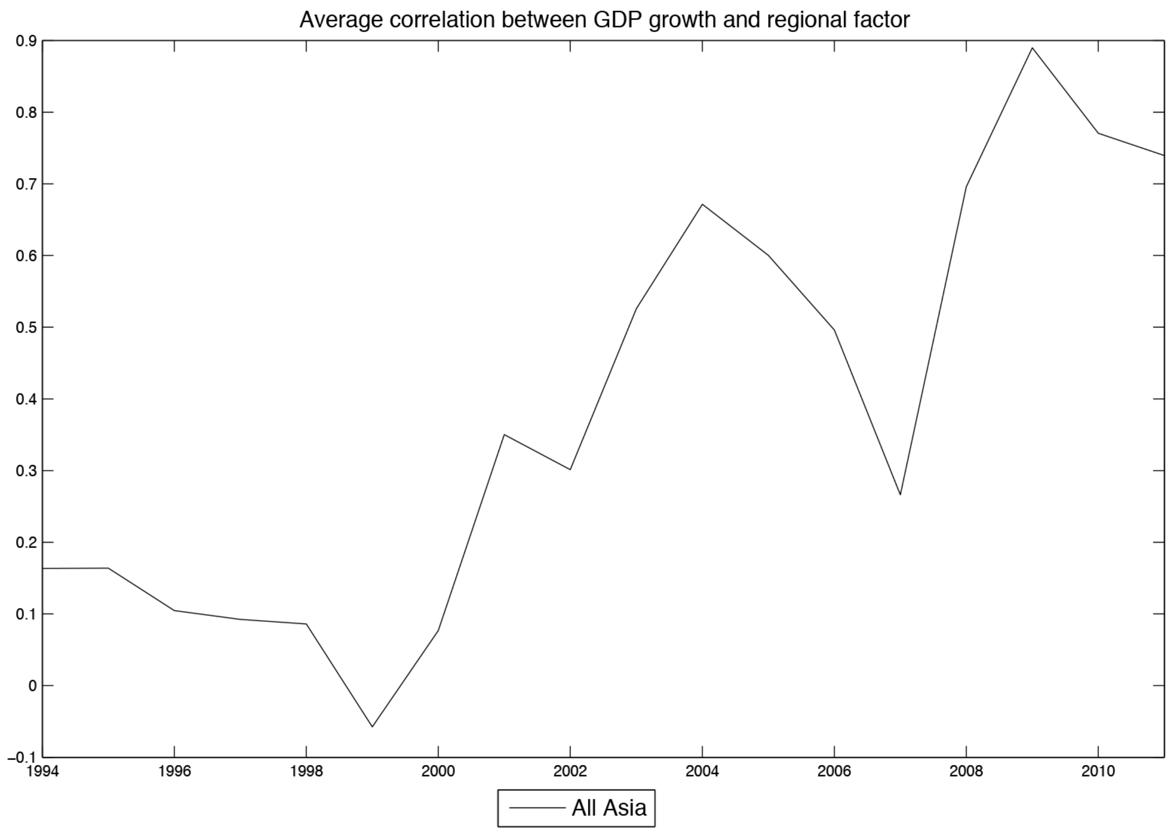

Figure 8. Average correlation between GDP growth and regional factor across Asia

4. Concluding Remarks

We have presented a model-based approach for capturing synchronicity attributable to global shocks and regional shocks. From a statistical standpoint, the method is desirable because it involves joint modeling and estimation of all model unknowns, thereby producing estimates that fully reflect parameter uncertainty, while also accounting for the co-movement and dynamic interdependence in the series. Our results indicate that both global shocks and regional shocks are playing a prominent role in determining output synchronization, with a higher share of output variance accounted for by regional shocks. Moreover, both shocks increasingly explain the output interdependence among Asian countries over the past two decades, which resulted in a higher degree of business cycle synchronization.

In order to examine the feasibility of a single currency union in Asia, we turn our attention to the symmetry of shocks by decomposing output variance into three distinct components: world component, regional component, and country-specific component. The intuition is that, if regional factors dominate output variance, then it would be less costly and more plausible to form a single currency in the region. Results indicate that, although Asia as a whole might not be a good candidate for a currency area, a subgroup of Asian countries (i.e., Malaysia, Indonesia and Thailand) appears more synchronized, thus more plausible for a single currency union.

In future research we intend to apply the proposed techniques to models containing additional macroeconomic indicators in order to capture a broader range of measures of business cycles. Moreover, higher frequency (e.g. quarterly or monthly) data will be employed to capture more dynamics in the growth cycle. Finally, the adequacy of more general dynamic specifications, such as models with variable-specific lags or time-variant parameters, will also be examined.

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Data Appendix

Non-Asia	East Asia	South Asia	Southeast Asia
United States	Taiwan	India	Malaysia
Germany	China	Bangladesh	Indonesia
Canada	Hong Kong	Pakistan	Philippines
France	Japan	Sri Lanka	Singapore
United Kingdom	Republic of Korea		Thailand

Notes: Annual Real GDP data over the period 1990-2011 are primarily drawn from the World Bank's World Development Indicators, supplemented with CEIC database.

Technical Appendix

Stacking Equation (1) over t, we have

$$Y = X\beta + (I_T \otimes A)F + \varepsilon, \varepsilon \sim N(0, I_T \otimes \Omega), \tag{7}$$

where$\beta = vec([\mu : B])', Y = (Y_1', \dots Y_T')', X = (X_1', \dots X_T')', F = (F_1', \dots, F_T')'$, and $\varepsilon = (\varepsilon_1', \dots, \varepsilon_T')'$.
(2) implies a joint density for F, which can be obtained by defining

$$H = \begin{pmatrix} I_k & & & & \\ -\Gamma & I_k & & & \\ & -\Gamma & I_k & & \\ & & \ddots & \ddots & \\ & & & -\Gamma & I_k \end{pmatrix}$$

and

$$S = \begin{pmatrix} D & & & & \\ & \Sigma & & & \\ & & \Sigma & & \\ & & & \ddots & \\ & & & & \Sigma \end{pmatrix}$$

so that (2) can be written as $HF = v$, where $v = (v_1', \dots, v_T')' \sim N(0, S)$. Therefore, a simple change of variable from v to F implies that

$$F|\Gamma, \Sigma \sim N(0, K^{-1})$$

and the precision matrix K is given by $K = H'S^{-1}H$, i.e.,

$$K = \begin{pmatrix} \Gamma'\Sigma^{-1}\Gamma + D_F^{-1} & -\Gamma'\Sigma^{-1} & & & \\ -\Sigma^{-1}\Gamma & \Gamma'\Sigma^{-1}\Gamma + \Sigma^{-1} & -\Gamma'\Sigma^{-1} & & \\ & \ddots & \ddots & \ddots & \\ & & -\Sigma^{-1}\Gamma & \Gamma'\Sigma^{-1}\Gamma + \Sigma^{-1} & -\Gamma'\Sigma^{-1} \\ & & & -\Sigma^{-1}\Gamma & \Sigma^{-1} \end{pmatrix}$$

$F_1 \sim N(0, D_F)$

Under Bayesian framework, parameters are treated as random variables whose means and variances are to be estimated from their posterior distributions. Since the analytic forms for the joint posterior of the unknowns are intractable, we generate draws by constructing a Markov chain which has the desired distribution as the equilibrium distribution. The state of the chain after a large number of steps is then used as a sample of the distribution of interest. In particular, the following MCMC sampler simulates draws from the posterior distribution of the factors and parameters in our model.

1) Sample $\beta|y,\ A,\ \Omega,\ \gamma, \sigma^2$

Rewrite (7) as

$$y = X\beta + u, u \sim N(0, \Sigma),$$

where $\Sigma = [(I_T \otimes \Omega) + (I_T \otimes A)K^{-1}(I_T \otimes A)']$.

$$[\beta|y,\theta]\sim N(\hat{\beta},\hat{B}),$$

with mean and variance given by

$$\hat{B}=(B_0^{-1}+X'\Sigma^{-1}X)^{-1} \text{ and } \hat{\beta}=\hat{B}(B_0^{-1}\beta_0+X'\Sigma^{-1}y)$$

Priors for β is given as $\beta\sim N(\beta_0,B_0)$.

2) Sample $F|y,\ \beta,\ A,\ \Omega,\ \gamma,\sigma^2$

Assume the prior for F is $F|\Gamma,\Sigma\sim N(0,K^{-1})$. Sample F from the following posterior distribution.

$$F|y,\theta\sim N(\hat{f},\hat{F})$$

with mean and variance given by

$$\hat{F}=\left(K+(I_T\otimes A)'(I_T\otimes\Omega^{-1})(I_T\otimes A)\right)'$$

and

$$\hat{f}=\hat{F}(I_T\otimes A)'(I_T\otimes\Omega^{-1})(y-X\beta)$$

3) Sample $\Omega|y,\ \beta,\ A,\ F$

Assume prior for ω_i as $\omega_i\sim IG(v_{i0}/2,\ r_{i0}/2)$. Draw samples of ω_i from the following posterior distribution.

$$\omega_i\sim IG((v_{i0}+T)/2\,,(r_{i0}+e_i'e_i)/2),$$

For i=1, . . ., n, where e_i is a T -vector of residuals from the ith observation equation.

4) Sample $\sigma^2|f,\ \gamma$

Assume prior for σ_i^2 as $\sigma_i^2\sim IG(s_{i0}/2\,,\delta_{i0}/2)$. The posterior distribution of σ_i^2 is given by

$$\sigma_i^2\sim IG((s_{i0}+T-1)/2\,,(\delta_{i0}+d_i'd_i)/2),$$

for i=1,. . ., K, where d_i is a (T-1)-vector of residuals from the ith transition equation.

5) Sample $\gamma|F,\ \sigma^2$

Denote γ as $\upsilon\mathrm{ec}(\Gamma')$. Assume prior $\gamma\sim N(0,\ \Gamma_0)1(\gamma\in S)$, where S is the region in which the eigenvalues of the companion matix Γ are less than one in absolute value.

The state equation is written as follows:

$$F_t=\Gamma F_{t-1}+v_t$$

Rewrite the state equation as

$$F_t'=F_{t-1}'\Gamma'+v_t'$$

Stack over *t* (excluding F_1'), we have

$$\begin{pmatrix} F_2' \\ F_3' \\ \vdots \\ F_T' \end{pmatrix} = \begin{pmatrix} F_1' \\ F_2' \\ \vdots \\ F_{T-1}' \end{pmatrix} \Gamma' + \begin{pmatrix} \nu_2' \\ \nu_3' \\ \vdots \\ \nu_T' \end{pmatrix}$$

Denote by

$$\widetilde{Y_F} = \begin{pmatrix} F_2' \\ F_3' \\ \vdots \\ F_T' \end{pmatrix}, X_F = \begin{pmatrix} F_1' \\ F_2' \\ \vdots \\ F_{T-1}' \end{pmatrix}, \widetilde{\nu} = \begin{pmatrix} \nu_1' \\ \nu_2' \\ \vdots \\ \nu_T' \end{pmatrix}$$

we have

$$\widetilde{Y_F} = X_F\Gamma' + \widetilde{v},\ \widetilde{v} \sim N(0, \Sigma \otimes I_{T-1})$$

Vectorize both sides,

$$vec\left(\widetilde{Y_F}\right) = vec(X_F\Gamma') + vec(\widetilde{v}),$$

which is

$$vec\left(\widetilde{Y_F}\right) = (I_K \otimes X_F)vec(\Gamma') + vec(\widetilde{v})$$

therefore,

$$\gamma|y, \theta \sim N\left(\hat{\gamma}, \hat{\Gamma}\right),$$

with mean and variance given by

$$\hat{\Gamma} = \left(\Gamma_0^{-1} + (I_K \otimes X_F')(\Sigma^{-1} \otimes I_{T-1})(I_K \otimes X_F)\right)^{-1}, \hat{\gamma} = \hat{\Gamma}\left((I_K \otimes X_F')(\Sigma^{-1} \otimes I_{T-1})vec\left(\widetilde{Y_F}\right)\right)$$

6) Sample $A|y,\ \beta,\ \Omega,\ \gamma, \sigma^2$

We have

$$y_{it} = \mu_i + \beta_1 y_{1t-1} + \ldots + \beta_i y_{it-1} + \ldots + \beta_n y_{nt-1} + a_i^g g_t + a_i^k f_t^k + \varepsilon_{it}$$

Stack over *i* and rewrite it as

$$Y_t = X_t\beta + A^g g_t + A^1 f_t^1 + \ldots + A^k f_t^K + \varepsilon_t$$

where K is the number of factors.

6.1) Sample A^g marginally of global factor g

For identification purpose, $A^g = (1, a')'$.

Stack the above equation over t,

$$Y - X\beta - (I_T \otimes A^1)F^1 - \ldots - (I_T \otimes A^K)F^K = (I_T \otimes A^g)g + \varepsilon,$$

Denoting by

$$Y_g = Y - X\beta - (I_T \otimes A^1)F^1 - \ldots - (I_T \otimes A^K)F^K,$$

we have

$$Y_g = (I_T \otimes A^g)g + \varepsilon$$

Sample $A^g|y,\ \theta_{\backslash g}$ marginally of g by MH with tailored proposal $a^\dagger \sim q(\hat{a}, V)$, and accept the proposed draw $a^\dagger$ with probability

$$aMH(a, a^\dagger) = min\left\{1, \frac{\pi\left(a^\dagger \middle| y, \theta_{\backslash g}\right) q(a|\hat{a}, V)}{\pi\left(a|y, \theta_{\backslash g}\right) q(a^\dagger|\hat{a}, V)}\right\}$$

6.2) Sample A^k marginally of regional factor f^k

For example, when k = 1, we sample A^1 by doing the following steps.

$$Y - X\beta - (I_T \otimes A^g)g - (I_T \otimes A^2)F^2 - \ldots - (I_T \otimes A^K)F^K = (I_T \otimes A^1)F^1 + \varepsilon$$

Denoting by

$$Y_{F1} = Y - X\beta - (I_T \otimes A^g)g - (I_T \otimes A^2)F^2 - \ldots - (I_T \otimes A^K)F^K,$$

we have

$$Y_{F1} = (I_T \otimes A^1)F^1 + \varepsilon$$

Denote $a1$ as the vector of the non-zero loadings for F^1. Sample $a1|y, \theta_{\backslash F1}$, marginally of F^1 by MH with tailored proposal $a1^\dagger \sim q\left(\widehat{a1}, V\right)$, and accept the proposed draw $a1^\dagger$ with probability

$$a1_{MH}(a1,\ a1^\dagger) = min\left\{1, \frac{\pi\left(a1^\dagger \middle| y,\ \theta_{\backslash F1}\right) q\left(a1|\widehat{a1}, V\right)}{\pi\left(a1|y,\ \theta_{\backslash F1}\right) q\left(a1^\dagger|\widehat{a1}, V\right)}\right\}$$