East Asian Currency Area: A Bayesian Dynamic Factor Model Analysis

Nguyen Ngoc Toan
Graduate School of Economics
Kyoto University

Background and Objective

- There has been a resurgence of interest in a concerted monetary arrangement and currency union in East Asia in the aftermath of the regional crisis.
  - The successful issuance of the Euro
  - The East Asian crisis shows that uncoordinated efforts could hardly win massive speculation
  - Increasing regional integration
- This paper assesses the feasibility and desirability of forming a currency area in East Asia by checking the symmetry of business cycles.

Why symmetry of business cycles is important?

- Joining a currency area involves a benefit and cost trade-off: the benefit is increasing trade and investment; the cost is foregoing independent monetary policy.
- Monetary policy is a major macroeconomic instrument to stabilize the economy, counter adverse shocks.
- If business cycles are symmetric, that is, they suffer largely from common shocks, a regional common policy is sufficient to counter shocks. Otherwise, one may have to rely on independent policy once sources of shocks are mainly country-specific.

How to measure shock symmetry: Structural VAR Approach

- **Methodology**: identifying structural shocks underlying aggregate variables (output, price…) using structural VAR due to Blanchard & Quah (1989) and computing bilateral correlations.
- **Previous studies**: Bayoumi & Eichengreen (1994), Sato *et al* (2003), Chow & Kim (2003)

Structural VAR: Disadvantages

- A representative country is needed as a proxy for a region (e.g. Japan for East Asia, Germany for EU).
- Bilateral correlation rather than regional symmetry.
- No separation of regional and world shocks
- Inherent problems with VAR approach (estimation, identification)

How to measure shock symmetry: Principle Component Approach

- Methodology: Using principle component analysis to measure the degree of confluence in several macroeconomic variables
- Previous studies: Goto & Hamada (1994), Goto (2002)
- Disadvantages: no distinction between regional and world causes.

How to measure shock symmetry: My Approach

- In my model, aggregate output is decomposed into (unobserved) common and idiosyncratic components: world component, regional component and country-specific component.
- Intuition: fluctuations in aggregate output are the consequences of shocks induced by either world or regional factors or factors that are specific to a particular country.
- Subsequent variance decomposition provides insight of the role of each components in output variance.
- Europe is used as a natural benchmark for comparision

My Model: Advantages

- Do not base on bilateral but on regional common factors. No representative country is needed.
- Separating the effects of world and regional factors.
- Analysis of world and regional business cycle dynamics is possible.

The Model: Assumptions (1)

- Aggregate output could be decomposed into world component, regional component and country-specific component. These components are contemporaneously uncorrelated.
- World and regional components influence differently in different countries, as indicated by corresponding coefficients.

$$y_{i,t} = \alpha_i W_t + \beta_i R_t^r + \varepsilon_{i,t}$$

The Model: Assumptions (2)

- The components follow stationary univariate first-order autoregressive representation.

$$W_t = aW_{t-1} + \eta_t^w, \quad \eta_t^w \sim N(0, \sigma_w^2)$$

$$R_t^r = b_r R_{t-1}^r + \eta_t^r, \quad \eta_t^r \sim N(0, \sigma_{R^r}^2)$$

$$\varepsilon_{i,t} = c_i \varepsilon_{i,t-1} + \eta_{i,t}, \quad \eta_{i,t} \sim N(0, \sigma_i^2)$$

The Model: State-Space Representation

- It is straightforward to cast the equations into state space form

$$\xi_t = F\xi_{t-1} + \nu_t$$
$$y_t = H\xi_t$$

where F and H are relevant coefficient matrices and

$$\xi_t = (W_t, R_t^1, R_t^2, R_t^3, R_t^4, \varepsilon_{1,t,}\varepsilon_{2,t,...,}\varepsilon_{n,t})'$$

The Model: Estimation (1)

- Note that in the above equations, only y_t is known. Other variables are not known so standard estimation techniques are not applicable.
- Traditional method using standard Kalman filter and log likelihood maximization is difficult to perform when cross-session dimension grows large.
- Bayesian approach with Gibbs sampling simulation allows us to work with large cross section data and large number of unknown parameters.

The Model: Estimation (2)

- Bayesian econometrics treats unknown parameters as random variables.
- The variables to be estimated are:
  - The stacked state vector $\tilde{\xi} = (\xi_1, \xi_{2,\ldots\ldots}\xi_T)'$
  - The parameters

$$\phi = (a, b_r, c_i, \sigma_w^2, \sigma_{R^r}^2, \sigma_i^2)$$

$$\psi = (\alpha_i, \beta_i)$$

- The posterior joint density of the random variables conditional on data is $p(\tilde{\xi}, \phi, \psi \mid \widetilde{Y})$

The Model: Estimation (3)

- The parameters are estimated by posterior simulation using Gibbs sampler
  - Conditional on the parameter vectors φ and ψ, draw state vector ξ from the conditional distribution p(ξ|φ, ψ,Y) using Durbin & Koopman (2002) simulation smoother.
  - Conditional on the state vector ξ, draw parameter vector φ from the conditional distribution p(φ|ξ,ψ,Y).
  - Conditional on the state vector ξ and the parameter vector φ, draw parameter vector ψ from the conditional distribution p(ψ|ξ,φ,Y).
- Step 2 and 3 are carried out using independent Normal – Gamma priors.These steps are iterated S times, of which the first So times are discarded as burning-in replications.

First step: Draw state vector ξ from the conditional distribution p(ξ|φ, ψ,Y) (1)

- Following Carter & Kohn (1994), p(ξ|φ, ψ,Y) is given by

$$p(\tilde{\xi} \mid \widetilde{Y}) = p(\xi_T \mid \widetilde{Y})\prod_{t=1}^{T-1} p(\xi_t \mid \xi_{t+1,} \widetilde{y_t}), \text{ where } \widetilde{y_t} = (y_{1,} y_{2,\ldots,} y_t)'$$

- Because our model is Gaussian

$$\xi_t \mid \widetilde{y_t} \sim N(\xi_{t|T,} P_{t|T}) \text{ or } \tilde{\xi} \mid \widetilde{Y} \sim N(\tilde{\xi}_{T,} \widetilde{P}_T) \text{ in stacked form}$$

$$\xi_{t|T} = E(\xi_t \mid \widetilde{yt}); \tilde{\xi}_T = (\xi_{1|T}, \xi_{2|T}, \ldots, \xi_{T-1|T,} \xi_{T|T})$$

First step: Draw state vector ξ from the conditional distribution p(ξ|φ, ψ,Y) (2)

- Recursive Kalman filter to derive $\xi_{t|T}$ and $P_{t|T}$

$$\xi_{t|t} = \xi_{t|t-1} + P_{t|t-1}H'(HP_{t|t-1}H' + R)^{-1}(y_t - H\xi_{t|t-1})$$

$$P_{t|t} = P_{t|t-1} - P_{t|t-1}H'(HP_{t|t-1}H' + R)^{-1} HP_{t|t-1}$$

$$\xi_{t+1|t} = F\xi_{t|t}$$

$$P_{t+1|t} = FP_{t|t}F' + Q$$

$$J_t = P_{t|t}F' P_{t+1|t}^{-1}$$

$$\xi_{t|T} = \hat{\xi}_{t|t} + J_t(\xi_{t+1|T} - \xi_{t+1|t})$$

$$P_{t|T} = P_{t|t} + J_t(P_{t+1|T} - P_{t+1|t})J_t'$$

First step: Draw state vector ξ from the conditional distribution p(ξ|φ, ψ,Y) (3)

- In principle, we could draw $\tilde{\xi}$ directly. However, generating $\tilde{\xi}$ from $\tilde{\xi} \mid \tilde{Y} \sim N(\tilde{\xi}_T, \tilde{P}_T)$ is not efficient and may sometimes face technical problems with the matrix.
- Durbin & Koopman (2002) has developed a more efficient simulation smoother which facilitate the drawing of $\tilde{\xi}$

Durbin & Koopman (2002) simulation smoother

- First, draw a random vector v^+ from $p(v) = N(0, Q)$ and recursively generate stacked vector $\tilde{\xi}^+$ and $\tilde{Y}^+$
- Second, compute $\tilde{\xi}_T = E(\tilde{\xi} \mid \tilde{Y})$ and $\tilde{\xi}_T^+ = E(\tilde{\xi}^+ \mid \tilde{Y}^+)$ using Kalman filter and smoother.
- Computing $\tilde{\xi} = \tilde{\xi}_T - \tilde{\xi}_T^+ + \tilde{\xi}^+$, we obtain a draw of $\tilde{\xi}$ from distribution

Identification Issues

- Two related identification problems should be solved when estimating the system:
  - The signs of the common components and their associated coefficients are not separately identified. We handle this by requiring one of the coefficients for each component to be positive.
  - The scale of the those components and coefficients are not separately identified either. We follow the convention to overcome this by normalizing the variances in world and regional component equations to unity.

Data

- This model is applied on an annual data set of 34 countries covering four regions: East Asia, Europe, North America and South America for the period from 1960 – 2002.
- The data is logged and first-differenced, demeaned and standardized to obtain mean zero and unit variance. Estimation program is written in Matlab code.

Sensitivity Analysis and Convergence

- Beside first-differencing, Hodrik – Prescott (1980) filter is used to ensure the results are not sensitive to filtering methods.
- Geweke (1992) numeric standard error and Raftery and Lewis (1992) Z-test confirm Gibbs sampling convergence.
- The Gibbs sampler is iterated 12,000 times, of which the first 2,000 is discarded as burning-in replications.

Result: Component Dynamics (1)

Figure 1: World Common Component

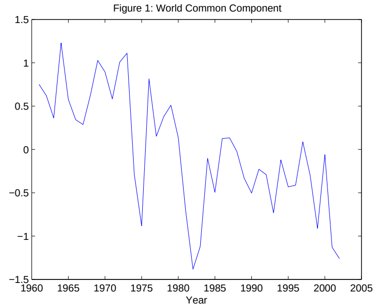
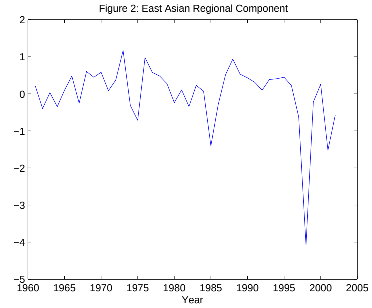


Figure 2: East Asian Regional Component



Result: Component Dynamics (2)

Figure 3: European Regional Component

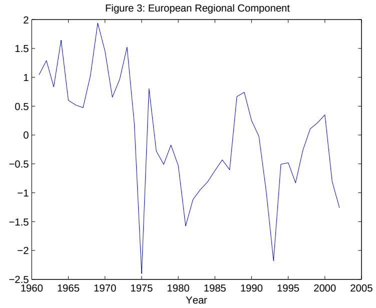


Figure 4: North American Regional Component

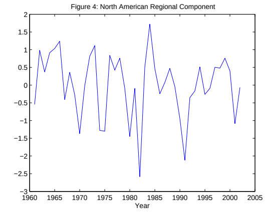
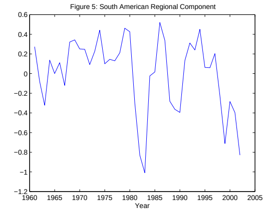


Figure 5: South American Regional Component



Result: Persistent Properties

- Regional components: Persistence is highest in Europe, followed by South America, East Asia and North America.
- Country-specific components (not shown): Persistence is lowest in Europe, followed by South and North America and East Asia.

World	0.4724
East Asia	0.2415
Europe	0.5092
Northern America	0.2308
Southern America	0.3578

Why Variance Decomposition is Necessary?

- To measure the role of world, regional and country-specific shocks in output volatility, variance decomposition analysis is conducted.
- If a large share of variance is explained by the regional component, a regional policy may serve all countries well.
- If a large share of variance is explained by the world component, joining a broader currency area may be justified.
- Otherwise, an independent monetary policy is necessary to reduce the cost of adjustment to shocks.

Variance Decomposition: Computation

$$Var(y_i) = \alpha_i^2 Var(W) + \beta_i^2 Var(R_r) + Var(\varepsilon_i)$$

$$Var(W) = \frac{1}{1-a^2}; Var(R_r) = \frac{1}{1-b_r^2}; Var(\varepsilon_i) = \frac{\sigma_i^2}{1-c_i^2}$$

$$Var(y_i) = \frac{\alpha_i^2}{1-a^2} + \frac{\beta_i^2}{1-b_r^2} + \frac{\sigma_i^2}{1-c_i^2}$$

$$S_i^w = \frac{\frac{\alpha_i^2}{1-a^2}}{Var(y_i)}; S_i^r = \frac{\frac{\beta_i^2}{1-b_r^2}}{Var(y_i)}; S_i = \frac{\frac{\sigma_i^2}{1-c_i^2}}{Var(y_i)}$$

Output Variance Decomposition

	World %	Regional %	Country-specific %
East Asian			
Japan	7.13	5.15	87.72
Korea	0.07	48.11	51.81
China	0.02	0.00	99.98
Hongkong	14.24	31.85	53.91
Singapore	1.36	37.84	60.80
Malaysia	1.44	67.15	31.41
Indonesia	0.06	45.92	54.02
Philippines	0.41	14.82	84.78
Thailand	0.00	54.99	45.01
Taiwan	17.92	16.02	66.05
Average	**4.26**	**32.19**	**63.55**
Europe			
Germany	15.73	83.10	1.17
Belgium	8.75	64.84	26.41
Finland	2.71	8.19	89.10
Neitherlands	6.28	55.52	38.21
France	5.89	71.52	22.60
Italy	6.16	46.35	47.50
Ireland	0.26	0.23	99.51
Spain	1.81	37.96	60.23
Portugal	6.19	42.60	51.20
Luxemburg	3.03	26.17	70.79
Austria	4.49	48.23	47.28
Greece	6.63	19.71	73.66
Average	**5.66**	**42.03**	**52.30**
North America			
US	3.32	95.66	1.02
Canada	4.24	77.13	18.63
Mexico	7.23	2.29	90.48
Average	**4.93**	**58.36**	**36.71**
Latin America			
Brazil	10.42	1.72	87.86
Argentina	9.08	5.49	85.43
Chile	2.54	2.47	95.00
Colombia	19.21	4.60	76.19
Peru	2.69	3.19	94.12
Uruguay	9.92	11.68	78.41
Paraguay	1.94	1.65	96.41
Venezuela	12.01	2.17	85.82
Bolivia	0.58	0.27	99.15
Average	**7.60**	**3.69**	**88.71**

Variance Decomposition: General Results

- Surprisingly, the world component, on average, merely accounts for less than 10 percent of fluctuations in all regions.
- Country-specific factors account for a large share in output variance in all regions. They explain 64 percent and 52 percent of variance in East Asia and Europe respectively.
- Regional components explain significant shares of variance in East Asia, Europe and North America.

Variance Decomposition: East Asia

- On average, East Asian regional component explains 32% of output variance.
- The regional component has negligible role in explaining output variance in China and Japan.
- Quite strong synchronization (48%) is found between East Asian NICs, except for Taiwan, where world shocks and country-specific shocks are more influential.

East Asia vs. Europe

- In general, East Asia exhibits less business cycle symmetry than Europe: variance share of regional component is lower and of country-specific component is higher.
- Adjustment speed to country-specific shocks in East Asia is slower and associating cost of adjustment is probably bigger.
- However, the gap between East Asia and Europe is not large. If we compare the highly synchronized group of Korea, HongKong, Singapore, Malaysia, Indonesia and Thailand with European average, the group appears even more suitable for a currency area.

Result: Juxtaposition

- Bayoumi & Eichengreen (1994), Goto & Hamada (1994) and Goto (2002) find that East Asia is as plausible candidate as Europe for a currency area.
- Sato et al (2003) find less persuasive support for a currency area in Asia and claim that only a subgroup of East Asian countries are possible candidates for monetary integration. They also find that adjustment speed to shocks is faster in East Asia.
- Chow and Kim (2003) shows that in East Asia, country-specific shocks are more important and therefore, joining a currency area is not optimal.

Conclusion

- East Asia is less plausible for a currency area than Europe.
- However, a subgroup of countries in East Asia might be suitable for a currency area since they show higher degree of synchronization.

Limitations and Scope for Improvement

- Since we work with output volatility in lieu of structural shocks, information on shocks might be conflated with policy responses.
- The model can be extended to map the components' disturbances into structural shocks, may be by using a Factor-Augmented VAR framework.
- The model could also be extended to capture the evolution of synchronization over time.
- More aggregate variables, such as consumption, investment and price could be introduced into the model.