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Measuring a Synchronization Parameter

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Business Cycle Spatial Synchronization: Measuring a Synchronization Parameter[*]

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Abstract
With decreasing comprehensive transportation costs, business cycle synchronization seems to be increasing. In such circumstances, we estimate business cycle synchronization of the Asia-Pacific region and European region. We apply the spatial generalized autoregressive score (Spatial GAS) method to measure the time-varying business cycle synchronization. Estimated business cycle synchronization parameters show positive high values in periods of economic turmoil, such as the collapse of the Lehman Brothers in 2008 by which high volatility is accompanied. With the recent increase in economic integration, exogenous shocks increased geographically and economically closer countries' business cycle synchronization to each other, and such shocks cause economic instability.

Keywords: Business cycle synchronization; Economic integration; Asia-Pacific; Time-varying spatial parameter; GAS model;
JEL classification: E32; F02; C23

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1 Introduction

During the last couple of decades, increased international trade, increased capital flows, economic integration, and financial markets openness have all occurred. The decline in transport costs have decreased economic distances and have increasingly integrated economies. One the one hand, in recent years, economic turmoil caused by crises, such as Asian Financial Crisis 1997 or collapse of Lehman Brothers in the United States on September 2008, has constituted a grave concern for policymakers. Such an exogenous shock causes economic instability to a greater or lesser degree. If economic distance has decreased, then business cycle synchronization might increase and economic shocks in one country might affect the respective economies of other countries more severely.

We specifically examine the Asia–Pacific business cycle synchronization because we recently have seen intensified trade or cross-border capital flows, business trips, and business transactions among Asia–Pacific countries. Therefore, the Asia–Pacific economy is apparently integrated to some degree. Actually, Asia–Pacific economic integration has proceeded. For instance, Free Trade Agreements (FTAs) and Economic Partnership Agreements (EPAs) are in force among several countries in the Asia–Pacific. The ASEAN Free Trade Area (AFTA) is now virtually established. Additionally, negotiation for Regional Comprehensive Economic Partnership (RCEP) is underway. The RCEP includes the 10 ASEAN countries, Japan, China, Korea Rep., Australia, New Zealand, and India. These integrations might intensify Asia–Pacific business cycle synchronization.

Many studies specifically examine business cycle synchronization. Frankel and Rose (1998), in their seminal study, explore the relationships between business cycle synchronizations which are measured using simple correlation coefficients of pairwise countries and their factors. Other studies which follow them also use correlation coefficients or some extended version of it as a proxy for business cycle synchronizations of pairwise countries and verify the causality between synchronizations and structural factors (Clark and Wincoop, 2001; Imbs, 2004, 2006; Kose and Yi, 2006; Baxter and Koupiratsas, 2005; Calderón et al., 2007; Inklaara et al., 2008; Cerqueira and Martins, 2009; Aritis and Okubo, 2011; Fidrmuc et al., 2012; Duval et al., 2016, Belke et al., 2017; and Gong and Kim, 2018). Frankel and Rose (1998) find a strong positive relation between intensified trade and business cycle synchronization.

These papers mainly shed light on G7 or OECD countries.[1] Some studies, such as those by Crosby (2003), Shin and Wang (2004), Kumakura (2006), Moneta and Rüffer (2009), Rana et al. (2012), and He and Liao (2012) specifically examine Asia or the Asia–Pacific region. Most of these studies also merely use a Pearson correlation or some extended version of it to gauge business cycle synchronization. Therefore, in many studies, the data are averaged over time; synchronization is defined as a pairwise cross-country correlation.

Stock and Watson (2005) analyze synchronizations of G7 business cycles using band-pass-filter for each G7 country and G7 average. They state that G7 business cycle is less synchronized for 30 years after the 1970s' greatest synchronization. However, the measurement of business cycle synchronization is basically also based on pairwise structure.

Meanwhile, Ductor and Leiva-Leon (2016) investigate the time-varying global synchronization. They conclude that the business cycle synchronization was moderate until the late 1990s, increased in the early 2000s, and it reached its maximum value at the end of 2008. This result is contrary to Stock and Watson (2005). Ductor and Leiva-Leon (2016) use the Leiva-Leon's (2017) approach which measures the business cycle synchronization of pairwise countries over time. Therefore, Ductor and Leiva-Leon (2016) also use the pairwise model, and they use pairwise synchronization for extracting a global business cycle synchronization indicator using simple averaging and principal component analysis. For this, they conduct a two-step calculation.[2] Furthermore, their first step in measuring pairwise synchronization is based on regime-switching model, i.e., measuring state: expansion or recession. Our focus is on synchronization of the level of business cycle, not on synchronization of the state of business cycle.

Badinger (2013) estimates the output volatility spillover effect parameter with a unique approach. He applies a spatial econometric method to the field of business cycle and interprets the "spatial parameter" as a volatility spillover effect. However, he merely applies cross-sectional spatial econometric method. Therefore, a lack of the information exists for the time dimension in estimating "spatial parameter". Additionally, because we

[1] Exceptions are Imbs (2004) who includes Peru, the Philippines, and South Africa among the 24 countries, Baxter and Koupiratsas (2004) include over 100 countries. Calderón et al. (2007) use 147 countries' data. Duval et al. (2016) assess 63 advanced and emerging economies. Gong and Kim (2018) cover East Asia, Latin America, and Central and Eastern Europe.

[2] They construct another more comprehensive method using dynamic factor models to extract the global factor. However, the output is still dependent on pairwise structure, i.e., movements between each country and global.

examine business cycle synchronization in the Asia–Pacific and EA, a lack of sample size occurs in the cross-sectional dimension if we use cross-sectional spatial econometric method. In this study, sample size for cross-sectional dimension is 13 for the Asia–Pacific and 11 for EA: we face severely insufficient sample size for estimation. In gauging Asia–Pacific business cycle synchronization and EA business cycle synchronization, panel datasets bring better sample size in estimation.

In this paper, we will take a different standpoint from that strand of studies. Instead of conducting structural analyses using data of trade intensity or structural similarity, we verify the relations between business cycle synchronization and volatility of the business cycle. Although most of earlier papers specifically present examination of long-term economic relations (because they averaged data for sub-sample span in calculating pairwise synchronizations), this paper specifically examines the short-run effects. This is due to the recent increment of large economic shocks and large volatility of business cycle, the earlier studies which focus on the long-term relations cannot capture such a short fluctuations. We regard that short-term fluctuations in business cycle is important factor for the synchronization of business cycle.

Although, synchronization as used in many papers stands for pairwise cross-country correlations, we define synchronization as a parameter among selected countries. Building on Badinger (2013), we use a more elaborate model: time-varying spatial parameter method.[3] Blasques et al. (2016) propose time-varying spatial parameter estimation. The estimation became possible using Generalized Autoregressive Score (GAS) models. This study would be the first application of time-varying spatial parameter in measuring business cycle synchronization. We calculate a synchronization parameter using a more elaborate one-step approach, unlike Ductor and Leiva-Leon (2016).

We will verify the following question. How would business cycle synchronization be affected by business cycle volatility or economic shocks? Business cycle volatility tends to be high during economic crises. Therefore, our prediction is that if some huge economic crisis occur and business cycle volatility is inflated, business cycles will move synchronously toward the same direction, i.e., acute downturn and rapid recovery. This is not precisely stated in earlier work conducted in this area. However, the work done by Ductor and Leiva-Leon (2016) is an exception, so we will re-examine the question. We also investigate whether business cycle synchronization increases with the degree of integration among countries or not. We compare the Asia–Pacific with EA, where countries are more closely integrated.

[3] Strictly speaking, definitions between "output volatility spillover effect" in Badinger (2013) and "business cycle synchronization" in this study are different.

The remainder of the paper is presented as follows. Section 2 states related studies, whereas Section 3 provides data and methods used for estimation. Section 4 presents estimation results. Section 5 states conclusions.

2 Related literature

We list the related literature, which specifically examines business cycle synchronization of the Asia–Pacific region.

Crosby (2003) examines GDP correlations between two countries, with an attempt to explain business cycle synchronization using some explanatory variables in a sample of 13 Asia–Pacific countries' annual data. The results show that trade is not an explanatory factor for correlations in the Asia–Pacific region but structural similarities among countries are determinant factors for business cycle correlations. Shin and Wang (2004) employ annual data for real GDP, which are collected for 12 Asian countries. Their finding is that increase in trade does not necessarily trigger close business cycle co-movements.

Kumakura (2006) verify the relationship between trade and business cycle correlations among 13 Asia–Pacific countries using annual GDP data. The findings show that, although trade accounts for international business cycle correlations, a more important determinant is the extent of specializations in the electronics industry. Moneta and Rüffer (2009) use a dynamic common factor model and extract common factors in real GDP growth using quarterly real GDP data for 10 Asian countries. They calculate correlation between GDP growth and common factors to elucidate the business cycle synchronization. They conclude that the synchronization appears to reflect strong export synchronization.

Rana et al. (2012) examine the relationship between trade intensities and business cycles synchronization in East Asia and Europe (EU-15). They use annual real GDP data for 10 East Asian countries and the EU-15. They conclude that intra-industry trade, rather than inter-industry trade, is the major explanatory factor for business cycle synchronization. He and Liao (2012) use quarterly data of real GDP of nine emerging Asian economies and G-7 countries. In measuring business cycle synchronization, they conduct variance decomposition and conclude that "although emerging Asian economies cannot decouple completely from the advanced economies, they have sustained a strong independent business cycle among themselves."

3 Data and methodology

3.1 Data description

In deciding the country range for the Asia–Pacific region, we follow RCEP. The selected 13 Asia–Pacific countries are Australia, China, Hong Kong, Indonesia, India, Japan, Korea Rep., Malaysia, New Zealand, Philippines, Singapore, Taiwan, and Thailand.[4] For EA, we select countries based on the Euro Area 11 that had adopted the Euro in 1999, Austria, Belgium, Germany, Spain, Finland, France, Ireland, Italy, Luxembourg, the Netherlands, and Portugal.

We use quarterly GDP data which correspond to the business cycle. The data are from 1996:Q4 – 2017:Q4 and are extracted from the "Global Economic Monitor", World Bank.[5] GDP is at market prices, constant 2010 local currency unit, millions and seasonally adjusted.[6] Because the output is known to be a non-stationary series, and to remove the linear trend for extracting short or medium-term fluctuation, we use the quarterly GDP growth rate.

In the Asia–Pacific case, we use one-quarterly lag of growth rate of the US GDP and EA common business cycle movement, for exogenous variables. In the EA case, we use one-quarterly lag of growth rate of the US GDP and Asia–Pacific common business cycle movement as exogenous variables. Common business cycle movement is calculated applying dynamic factor model for which we describe steps at Section 3.

Figure 1 depicts the GDP quarterly growth rates of Asia–Pacific countries. A downward trend is found around 1997 (Asian Financial Crisis) and around 2008 through 2009 (Collapse of Lehman Brothers in the United States (US) on September 2008). A dispersed trend is apparent elsewhere. Figure 2 shows the quarterly GDP growth rates of EA countries. A downturn is also apparent at around 2008–2009, but not around 1997. A downward trend during 2008–2009 is clearer in EA than in the Asia–Pacific.

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[4] Because of difficulties in data availability, the other countries defined in RCEP are excluded.

[5] Data for India is only from 1996:Q2.

[6] Data of Malaysia is from 2005:Q1only. Therefore, we also use GDP growth (year-on-year, %) data from ADB "Economic and Financial Indicators"; we obtain Malaysia's GDP data during 1993:Q2 – 2004:Q4 by calculating backward and seasonally adjusting with X-13ARIMA-SEATS.

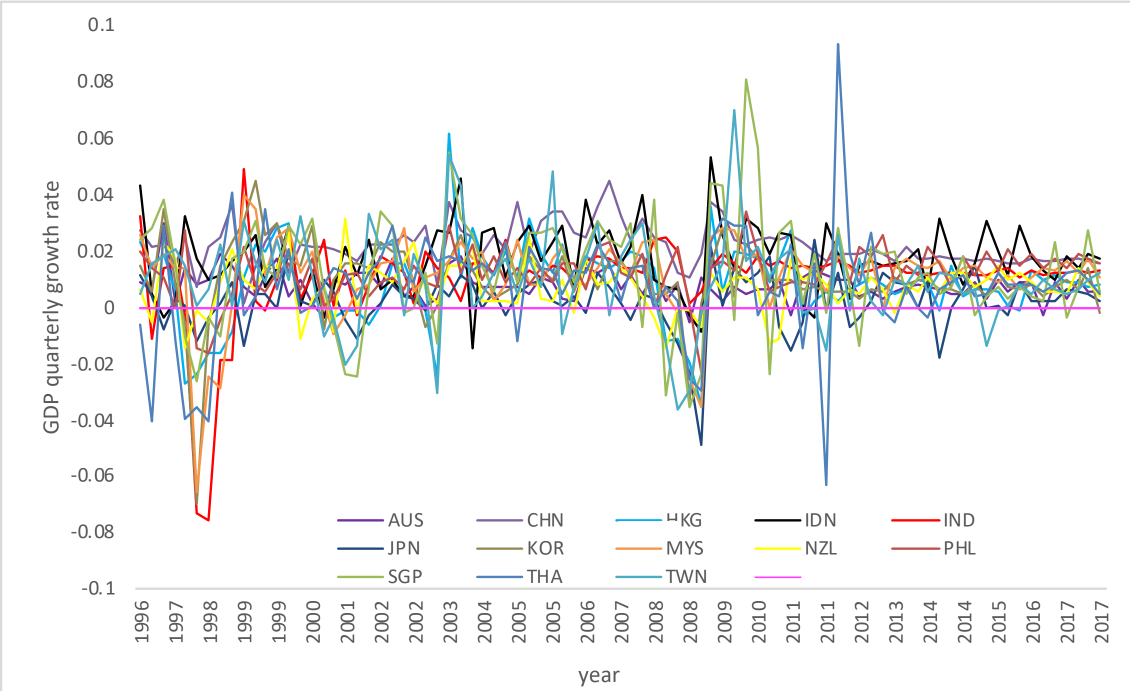

Figure 1 GDP quarterly growth rates of Asia–Pacific countries (1994:Q4 – 2017:Q4)

Note: Data are from 1996:Q4 – 2017:Q4 and are extracted from "Global Economic Monitor", World Bank. GDPs are at market prices, constant 2010 local currency unit, millions and seasonally adjusted. GDP is the growth rate. Country codes and names: AUS, Australia; CHN, China; HKG, Hong Kong; IDN, Indonesia; IND, India; JPN, Japan; KOR, Korea Rep.; MYS, Malaysia; NZL, New Zealand; PHL, Philippines; SGP, Singapore; THA, Thailand; and TWN, Taiwan.

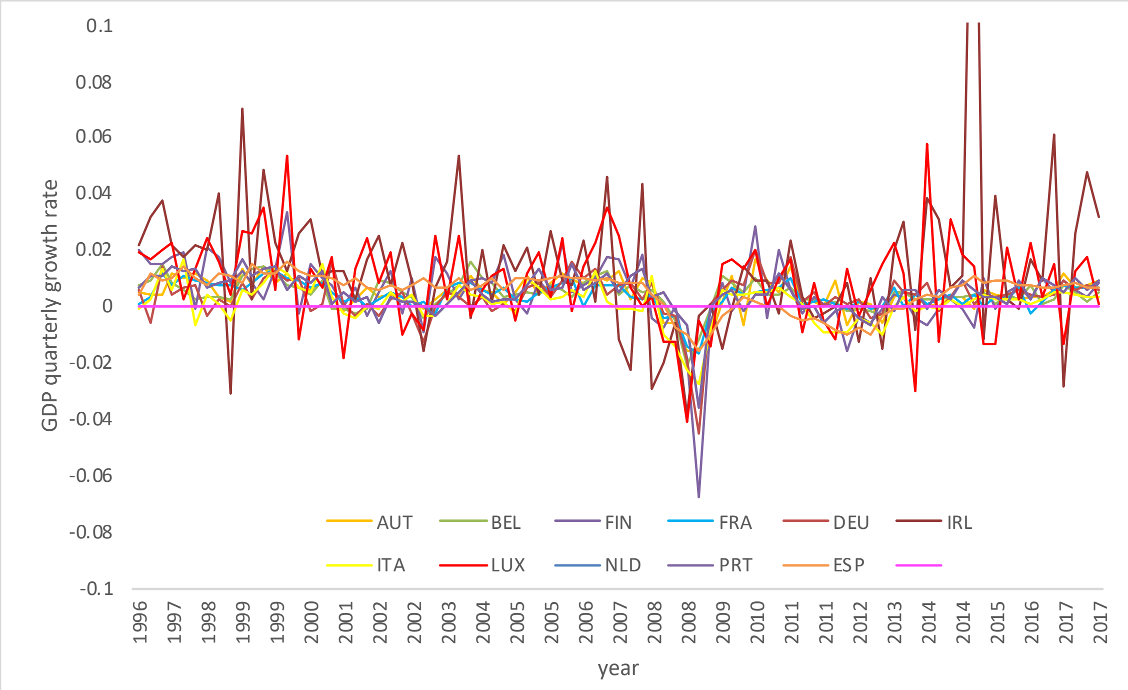

Figure 2 GDP quarterly growth rates of Euro Area 11 countries (1994:Q4 – 2017:Q4)

Note: Data are from 1996:Q4 – 2017:Q4 and are extracted from "Global Economic Monitor", World Bank. GDPs are at market prices, constant 2010 local currency unit, millions and seasonally adjusted. GDP is the growth rate. Country codes and names: AUT, Austria; BEL, Belgium; DEU, Germany; ESP, Spain; FIN, Finland; FRA, France; IRL, Ireland; ITA, Italy; LUX, Luxembourg; NLD, The Netherlands; and PRT, Portugal.

Descriptive statistics are presented in Table 1 and 2. For the Asia–Pacific, high growth is found in China, India, Singapore, and other countries. Singapore, Thailand, and Taiwan show high standard deviations. For the EA, Ireland and Luxembourg show high growth rates. Standard deviations are high for Ireland, Luxembourg, and Finland.

Table 1 Descriptive statistics of GDP quarterly growth rates of Asia–Pacific countries (1996:Q4 – 2017:Q4)

	Mean	Standard deviation	Median	Max	Min
AUS	0.008	0.005	0.007	0.030	−0.005
CHN	0.022	0.007	0.021	0.045	0.001
HKG	0.008	0.014	0.009	0.061	−0.034
IDN	0.017	0.012	0.017	0.053	−0.014
IND	0.010	0.016	0.013	0.049	−0.076
JPN	0.002	0.010	0.003	0.024	−0.049
KOR	0.010	0.014	0.009	0.045	−0.070
MYS	0.011	0.015	0.014	0.040	−0.065
NZL	0.007	0.009	0.008	0.032	−0.015
PHL	0.012	0.009	0.013	0.034	−0.023
SGP	0.013	0.020	0.012	0.081	−0.036
THA	0.008	0.020	0.009	0.094	−0.063
TWN	0.010	0.017	0.009	0.070	−0.037

Note: Data are from 1996:Q4 – 2017:Q4 and are extracted from "Global Economic Monitor", World Bank. GDPs are at market prices, constant 2010 local currency unit, millions and seasonally adjusted. GDP is the growth rate. Country codes and names: AUS, Australia; CHN, China; HKG, Hong Kong; IDN, Indonesia; IND, India; JPN, Japan; KOR, Korea Rep.; MYS, Malaysia; NZL, New Zealand; PHL, Philippines; SGP, Singapore; THA, Thailand; and TWN, Taiwan.

Table 2 Descriptive statistics of GDP quarterly growth rates of Euro Area 11 countries (1996:Q4 – 2017:Q4)

	Mean	Standard deviation	Median	Max	Min
AUT	0.005	0.006	0.005	0.017	−0.015
BEL	0.004	0.005	0.004	0.016	−0.021
DEU	0.004	0.008	0.004	0.020	−0.045
ESP	0.005	0.007	0.008	0.016	−0.016
FIN	0.005	0.012	0.005	0.034	−0.068
FRA	0.004	0.005	0.004	0.013	−0.016
IRL	0.015	0.030	0.011	0.217	−0.038
ITA	0.001	0.007	0.002	0.016	−0.028
LUX	0.009	0.016	0.012	0.057	−0.041
NLD	0.005	0.007	0.005	0.017	−0.036
PRT	0.003	0.008	0.004	0.022	−0.023

Note: Data are from 1996:Q4 – 2017:Q4 and are extracted from "Global Economic Monitor", World Bank. GDPs are at market prices, constant 2010 local currency unit, millions and seasonally adjusted. GDP is the growth rate. Country codes and names: AUT, Austria; BEL, Belgium; DEU, Germany; ESP, Spain; FIN, Finland; FRA, France; IRL, Ireland; ITA, Italy; LUX, Luxembourg; NLD, The Netherlands; and PRT, Portugal.

We present simple correlation coefficients of GDP quarterly growth rates in Tables 3 and 4.

High correlation is found for Malaysia and Hong Kong, Malaysia and Indonesia, and Singapore and Malaysia. These countries are known as Indonesia–Malaysia–Singapore Growth Triangle. Singapore, Hong Kong, and Malaysia also show high correlation. A main driving force for their economies is known as China funds: a common feature for these countries. Other strong relations are apparent for Malaysia and Korea Rep. and Singapore and Korea Rep.

Turning to EA, an interesting feature is that the correlation is higher than Asia–Pacific, in general. Exceptions are Ireland and Luxembourg. Furthermore, Spain and Germany and Portugal and Germany exhibit low correlation.

Table 3 Correlation of GDP quarterly growth rates of Asia–Pacific countries (1996:Q4 – 2017:Q4)

	AUS	CHN	HKG	IDN	IND	JPN	KOR	MYS	NZL	PHL	SGP	THA	TWN
AUS													
CHN	0.247												
HKG	0.042	0.377											
IDN	0.015	0.257	0.293										
IND	−0.152	0.040	0.404	0.109									
JPN	0.034	0.260	0.428	0.258	0.148								
KOR	0.298	0.298	0.492	0.177	0.459	0.243							
MYS	−0.028	0.241	0.620	0.298	0.683	0.418	0.688						
NZL	0.137	0.047	0.420	0.087	0.174	0.203	0.350	0.260					
PHL	−0.034	0.140	0.446	0.334	0.513	0.396	0.334	0.606	0.182				
SGP	0.161	0.356	0.648	0.266	0.291	0.373	0.505	0.546	0.296	0.395			
THA	0.107	0.240	0.349	0.104	0.345	0.350	0.386	0.368	0.358	0.293	0.368		
TWN	0.283	0.308	0.443	0.217	0.051	0.213	0.295	0.333	0.124	0.120	0.441	0.272	

Note: Data are from 1996:Q4 – 2017:Q4 and are extracted from "Global Economic Monitor", World Bank. GDPs are at market prices, constant 2010 local currency unit, millions and seasonally adjusted. GDP is the growth rate. Country codes and names: AUS, Australia; CHN, China; HKG, Hong Kong; IDN, Indonesia; IND, India; JPN, Japan; KOR, Korea Rep.; MYS, Malaysia; NZL, New Zealand; PHL, Philippines; SGP, Singapore; THA, Thailand; and TWN, Taiwan. Densely shaded cell shows higher correlation.

Table 4 Correlation of GDP quarterly growth rates of Euro Area 11 countries (1996:Q4 – 2017:Q4)

	AUT	BEL	DEU	ESP	FIN	FRA	IRL	ITA	LUX	NLD	PRT
AUT											
BEL	0.711										
DEU	0.647	0.593									
ESP	0.554	0.541	0.390								
FIN	0.615	0.582	0.627	0.578							
FRA	0.736	0.710	0.696	0.637	0.661						
IRL	0.172	0.246	0.136	0.304	0.077	0.252					
ITA	0.699	0.757	0.693	0.684	0.633	0.780	0.259				
LUX	0.396	0.455	0.355	0.364	0.399	0.381	0.313	0.398			
NLD	0.628	0.590	0.658	0.666	0.666	0.720	0.227	0.678	0.229		
PRT	0.508	0.493	0.370	0.659	0.584	0.579	0.266	0.535	0.317	0.657	

Note: Data are from 1996:Q4 – 2017:Q4 and are extracted from "Global Economic Monitor", World Bank. GDPs are at market prices, constant 2010 local currency unit, millions and seasonally adjusted. GDP is the growth rate. Country codes and names: AUT, Austria; BEL, Belgium; DEU, Germany; ESP, Spain; FIN, Finland; FRA, France; IRL, Ireland; ITA, Italy; LUX, Luxembourg; NLD, The Netherlands; and PRT, Portugal.

3.2 Spatial GAS model

Many studies incorporate the distance or geographic adjacency among countries, or gravity-like variables (Frankel and Rose, 1998; Clark and Wincoop, 2001; Imbs, 2004, 2006; Baxter and Koupiratsas, 2005; Calderón et al., 2007; Inklaara et al., 2008; and Fidrmuc et al., 2012). Similarly to this, Kose and Yi (2006) employ transportation costs. In this manner, although geographical distance or spatial heterogeneity is substantial in business cycle synchronization, few studies use spatial econometric methods.

In this paper, we utilize spatial econometric method to incorporate the geographical and economic distance among countries using spatial weight matrix. To measure business cycle synchronization, we estimate the time-varying spatial parameter. Blasques et al. (2016) propose time-varying spatial parameter estimation. The estimation becomes possible using Generalized Autoregressive Score (GAS) models, which have been applied in many areas, including modeling time-varying dependence structures. The GAS model is proposed by Creal et al. (2008).[7] The GAS model is based on the score and likelihood evaluation is straightforward in the GAS model.

Blasques et al. (2016) extend the static Spatial Durbin model (SDM) by introducing a time-varying spatial dependence parameter. The SDM for panel data is

$$y_t = \rho W y_t + \beta_1 \iota_n + A_t \beta_2 + W A_t \beta_3 + e_t,$$
$$e_t \sim p_e(e_t;\ \Sigma,\ \lambda),\ t = 1,\ \cdots,\ T, \qquad (1)$$

[7] A revised paper is published as Creal et al. (2012).

where $y_t = (y_{1t}, \cdots, y_{nt})'$ is a vector of the dependent variable observed for n cross-section and t represents time dimension, ρ denotes spatial dependence parameter, W stands for an $n \times n$ spatial weight matrix, β_1 is constant, ι_n expresses vector of 1s, A_t is $n \times k$ exogenous variables, β_2 and β_3 are parameters, and e_t signifies an $n \times 1$ vector of error component with density $p_e(e_t; \Sigma, \lambda)$, mean zero, unknown $k \times k$ covariance matrix Σ, and parameter vector λ.

We rewrite the SDM model as

$$y_t = \rho W y_t + X_t \beta + e_t \quad (2)$$

where $X_t \coloneqq (\iota_n : A_t : W A_t)$ and $\beta \coloneqq (\beta_1, \beta_2', \beta_3')'$. DGP of the SDM model is,

$$y_t = (I_n - \rho W)^{-1} X_t \beta + (I_n - \rho W)^{-1} e_t.$$

We reform the model (2) with introduction of time-varying spatial parameter ρ_t as

$$\begin{gathered} y_t = \rho_t W y_t + X_t \beta + e_t \\ e_t \sim p_e(e_t; \Sigma, \lambda),\ t = 1, \cdots, T, \quad (3) \end{gathered}$$

where $\rho_t = h(f_t)$ is a monotonic transformation of time-varying parameter f_t. An appropriate link function $h(\cdot)$ is chosen such that $\rho_t \in (-1, 1)$.

The GAS framework is adoptable by estimating the time-varying parameter f_t. The updating equation of f_t is

$$f_{t+1} = \omega + A s_t + B f_t, \quad (4)$$

where ω is a constant and A and B are unknown parameters, and where $s_t = S_t \cdot \nabla_t$ is a scaled score function.

The scaled score function is the first derivative of the log-likelihood function at time *t* with respect to f_t. The score function is given as $\nabla_t = \frac{\partial \ell_t}{\partial \rho_t} \cdot \frac{\partial h(f_t)}{\partial f_t}$, where $\rho_t = h(f_t)$ and

$$\ell_t = \ln p_e(y_t - \rho_t W y_t - X_t \beta, \Sigma; \lambda) + \ln |(I_n - \rho_t W)|. \quad (5)$$

Blasques et al. (2016) use unit scaling such that $S_t \coloneqq 1$ and $s_t = \nabla_t$. The log determinant term accounts for the nonlinearity of the model in ρ_t.

Vectors of static parameters are defined as $\theta \coloneqq (\omega,\ A,\ B,\ \beta,\ \lambda)'$. Numerical maximization is used to estimate θ with the likelihood function shown below as

$$\mathcal{L}_T = \sum_{t=1}^{T} \ell_t. \quad (6)$$

We consider the multivariate normal distribution for density p_e.[8] The log-likelihood function using the multivariate normal distribution is obtained as

$$\ell_t = \ln|(I_n - h(f_t)W)| - \frac{n}{2}\ln(2\pi) - \frac{1}{2}\ln|\Sigma| \\ - \frac{1}{2}(y_t - h(f_t)Wy_t - X_t\beta)'\Sigma^{-1}(y_t - h(f_t)Wy_t - X_t\beta). \quad (7)$$

The score function is

$$\nabla_t = \left(y_t'W'\Sigma^{-1}(y_t - h(f_t)Wy_t - X_t\beta) - tr(Z(f_t)W)\right) \cdot \dot{h}(f_t), \quad (8)$$

where $tr\,(\cdot)$ is the trace operator, $Z(f_t) = (I_n - h(f_t)W)^{-1}$, and where $\dot{h}(f_t)$ is the first derivative of the transformation function h with respect to f_t.

If $h(f_t) = \gamma\tanh(f_t)$ with $\gamma \in (0,\ 1)$, then $\dot{h}(f_t) = \gamma(1 - \tanh^2(f_t))$, where $\tanh(\cdot)$ is a hyperbolic tangent function.

Finally, the feasible score function is shown below

$$s_t = \nabla_t = \left(y_t'W'\Sigma^{-1}\left(y_t - \gamma\frac{e^{f_t} - e^{-f_t}}{e^{f_t} + e^{-f_t}}Wy_t - X_t\beta\right) \right. \\ \left. - tr\left(\left(I_n - \gamma\frac{e^{f_t} - e^{-f_t}}{e^{f_t} + e^{-f_t}}W\right)^{-1} W\right)\right) \cdot \gamma\left(1 - \left(\frac{e^{f_t} - e^{-f_t}}{e^{f_t} + e^{-f_t}}\right)^2\right). \quad (9)$$

[8] Multivariate *t*-distribution is also considered by Blasques et al. (2016).

We designate this model as the Spatial GAS model. For estimation, we set adequate starting values for each parameter and f_t and evaluate log-likelihood for each period (we call this step local evaluation) and estimate parameters with optimization associated with equation (7) (we call this global evaluation).[9]

We incorporate spatial weight matrix W in the model. For our study, the spatial weight matrix is specified as the inverse distance and export value between countries i and j.

Business cycles of geographically nearer countries and those with higher trade intensity are more influential than those of distant and less trade-intensive countries. Therefore, if ρ_t shows a high value, then the geographically or economically closer countries' business cycles are synchronized. In other words, ρ_t corresponds to the spatial dependence of business cycles among countries. Consequently, ρ_t represents the degree of business cycle synchronization in our context.

If ρ_t is negative, then the closer countries' business cycles move in opposite directions. If the value of ρ_t is close to 0, the business cycles are dispersed so no spatial dependence is found. We are able to estimate a time-varying business cycle synchronization parameter through a spatial econometric model, with accompanying spatial parameters. The merit for the Spatial GAS model is in using information of the full sample.

3.3 Spatial panel model

To complement our main results, we use spatial panel econometric methods (Anselin, 2001; Baltagi et al., 2003; Elhorst, 2003, 2009; and Anselin et al., 2008).

We describe the spatial panel model as

$$y = \rho(I_t \otimes W_n)y + X\beta + u. \qquad (10)$$

This is the spatial autoregressive (SAR) structure for which y is an $nt \times 1$ dependent variable and X is an explanatory variable of the $nt \times k$ matrix. Also, ρ corresponds to spatial dependence parameter of autoregressive process with $|\rho| < 1$, I_t is the identity matrix with dimension t, and W_n is the $n \times n$ spatial weight matrix. Altogether, in each time period, we have $n \times n$ spatial weight matrices.

$u\ of\ equation\ (10)$ is the disturbance vector written as

$$u = (\iota_t \otimes I_n)\mu + \varepsilon, \qquad (11)$$

[9] We choose "simulated annealing" as an optimization method.

where ι_t represents a $t \times 1$ vector of ones, I_n denotes the $n \times n$ identity matrix, μ stands for a vector of time-invariant individual specific effects, and ε_{it} follows $\varepsilon_{it} \sim \mathrm{N}\ (0, \sigma^2)$. In each time period, we have identity matrix with dimension n, which is associated with μ the vector of individual specific effects. This model depicts a one-way error component. Estimation is conducted via maximum likelihood method.

Actually, W_n is fixed over time, if one uses rolling estimation, then this parameter ρ moves toward the time period.

3.4 Estimation strategy

We respectively estimate time-varying spatial parameter ρ_t for 13 countries in the Asia–Pacific region and 11 countries in EA.

For estimation of the Spatial GAS model, we set the main equation as

$$y_{it} = \rho_t \sum_{j=1}^{N} w_{ij}\, y_{jt} + \beta_1 x_{1t-1} + \beta_2 x_{2t-1} + e_{\mathrm{it}},$$

$$e_t \sim N(0, \sigma^2) \qquad (12)$$

where y_{it} stands for the GDP quarterly growth rate in the Asia–Pacific region or EA, y_{jt} expresses growth rate of the other countries' quarterly GDP in the Asia–Pacific region or EA accompanied by spatial weight matrix W_n, ρ_t denotes the time-varying spatial parameter, i.e. synchronization parameter, w_{ij} stands for components of $n \times n$ inverse distance weight matrix W_n, x_{1t-1} signifies the one-quarter lag of growth rate of GDP of the US, x_{2t-1} represents the one-quarter lag of common business cycle movement of EA for the Asia–Pacific dataset, one-quarter lag of common business cycle movement of the Asia–Pacific for EA dataset, β_1, β_2 is a parameter, and e_{it} represents the idiosyncratic error. The sample period is 1996:Q4 – 2017:Q4. The sample size is 85 for the time dimension.

The spatial weight matrix is $W_n = W_n^d \circ W_n^e$, where W_n^d is the spatial weight matrix of distance and W_n^e is the spatial weight matrix of export value. Each element of spatial weight matrix W_n is $w_{ij} = w_{ij}^e w_{ij}^d$. Diagonal elements of W_n are set to 0 and as a convention, each row of W_n is normalized to 1.[10]

Off-diagonal elements of W_n^d, distance, denote the inverse distance of 1000 km

[10] To be precise, each W_n^d and W_n^e are row normalized to 1, and we produce them to make W_n; finally W_n is row normalized again to 1.

unit between countries i and j and are expressed as a gravity-like model,

$$w_{ij}^{d} = 1/dist_{ij}^{2}, \qquad i \neq j. \qquad (13)$$

(Anselin, 2002), where $dist_{ij}$ is the distance separating countries i and j. Here, CEPII's GeoDist is used for bilateral distance data: the distance between countries' respective capitals.[11]

Off-diagonal elements of W_n^e are export values, which are calculated as

$$w_{ij}^{e} = \frac{export_{ij} + export_{ji}}{2}, \qquad (14)$$

where $export_{ij}$ represents the export value from country i to j; $export_{ji}$ is the export value from country j to i. The export value is extracted from the United Nations Conference on Trade and Development. Data are in thousands of United States dollars and are annual so that the data are averaged over the sample period.

Common business cycle movements in the Asia–Pacific and EA are estimated through a dynamic factor model. A simple dynamic factor model in state-space representation is presented in equations (15) and (16).

$$x_t = x_{t-1} + w_t, \quad w_t \sim MVN(0, \Omega) \qquad (15)$$
$$y_t = Zx_t + v_t, \quad v_t \sim MVN(0, R), \qquad (16)$$

where y_t represents the GDP growth rate, x_t stands for a hidden trend (i.e. common business cycle movement), and Z denotes factor loadings. The model is estimated via a Kalman filter.

A common movement is estimated using each country's GDP growth rate, so the common movements can be interpreted as an approximation of the Asia–Pacific or EA GDP growth rates.

For spatial panel method, we estimate the following spatial autoregressive (SAR) type equation as

[11] Mayer, T. and Zignago, S. (2011) "Notes on CEPII's distances measures: the GeoDist Database," *CEPII Working Paper*, 2011-25.

$$y_{it} = \rho \sum_{j=1}^{N} w_{ij}\, y_{jt} + \beta_1 x_{1t-1} + \beta_2 x_{2t-1} + u_{\mathrm{it}},$$

$$u_{it} = \mu_i + \varepsilon_{it},\ \ \varepsilon_{it} \sim N(0, \sigma^2), \qquad (17)$$

where the notations for y_{it}, w_{ij}, x_{1t-1}, and x_{2t-1} are the same as those of equation (12) above. In addition, ρ is a spatial parameter, μ_i represents time-invariant individual specific effects, and ε_{it} is the idiosyncratic error.

For retaining the sample size, spatial panel estimation is conducted with *T*=8, i.e., the time span will be two years. We shift the time window from 1996:Q4 – 1997:Q4, 1997:Q1 – 1998:Q1, …, 2016:Q4 – 2017:Q4. Therefore, the estimation will be conducted several times, i.e. rolling estimation will be conducted.

4 Estimation results and discussion

4.1 Basic results

Results obtained for the Asia–Pacific region are shown in Figure 3. Those for EA are shown in Figure 4. Estimated *rho* (ρ_t) by Spatial GAS model (*S-GAS rho* hereafter), *rhos* (ρ) by spatial panel model (*SAR-8 rho* hereafter), and common business cycle movements (*CO* hereafter) are depicted in Figures 3 and 4. Hereafter, a point of times displayed in figures present $\left(\frac{1}{2}\mathrm{T} + 1\right)^{\mathrm{th}}$ periods of each spatial panel estimation, i.e. for *T*=8, the fifth period.

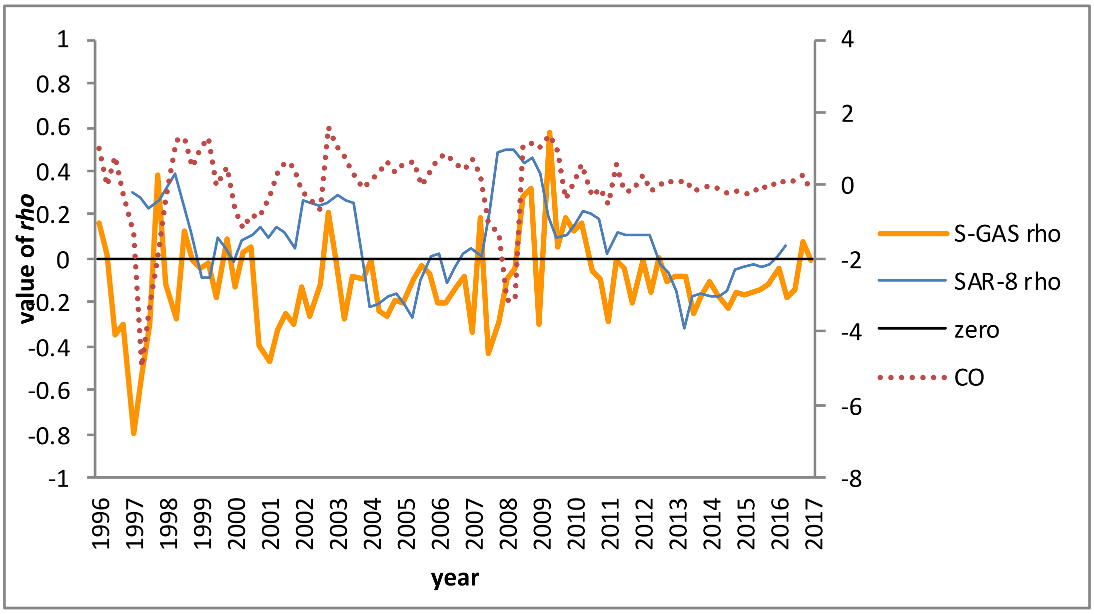

Figure 3 Estimated synchronization parameter for the Asia–Pacific using Spatial GAS model and spatial panel method and the common business cycle movements in the Asia–Pacific

Note: *S-GAS rho* is estimated *rho* under Spatial GAS model and *SAR-8 rho* is estimated *rhos* under spatial panel model with $\mathrm{T} = 8$. *CO* is the estimated common business cycle movements in the Asia–Pacific via a Kalman filter. The scale of *CO* is on the right side vertical axis. The horizontal axis means $\left(\frac{1}{2}\mathrm{T}+1\right)^{\mathrm{th}}$ of the estimated period for estimated *rhos* under spatial panel model: 2009:Q1 means 2008:Q1 – 2009:Q4 for T=8.

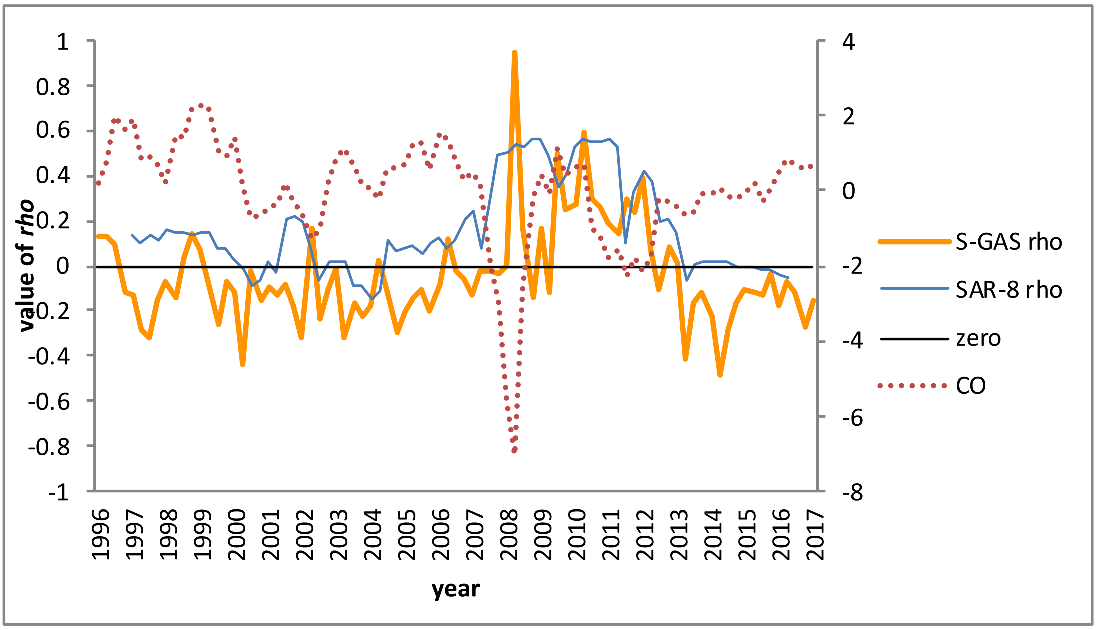

Figure 4 Estimated synchronization parameter for Euro Area using Spatial GAS model and spatial panel method and common business cycle movements in Euro Area

Note: *S-GAS rho* is estimated *rho* under Spatial GAS model and *SAR-8 rho* is estimated *rhos* under spatial panel model with $\mathrm{T}=8$. *CO* is the estimated common business cycle movements in Euro Area via a Kalman filter. Scale of *CO* is on the right-side vertical axis. The horizontal axis means $\left(\frac{1}{2}\mathrm{T}+1\right)^{\mathrm{th}}$ of the estimated period for estimated *rhos* under spatial panel model, e.g., 2009:Q1 means 2008:Q1 – 2009:Q4 for T=8.

The results in Figure 3 show that for the Asia–Pacific case, *S-GAS rho* climbs steeply in late 1997 to early 1998 and reaches its peak in 1998:Q3. Another peak is found around 2008 through 2010. The first peak of *S-GAS rho* is in 2008:Q1. The second peak is in 2010:Q1. The first wave corresponds to the recession from Asian Financial Crisis on 1997. This result is in accordance with Moneta and Rüffer (2009), who pointed out that the "Asian crisis clearly caused an increase in overall synchronization." The second wave stems from the shock by collapse of Lehman Brothers in September 2008. The other peak is in 2003:Q3, caused by the collapse of the dot-com bubble (or internet bubble).

SAR-8 rho from spatial panel model shows a similar tendency, but the peaks of the wave differ slightly from those of earlier obtained results. Furthermore, from our estimation approach, the wave is loose because *SAR-8 rho* is averaged over two years. CO (dotted line) in the Asia–Pacific shows a great recession occurred in 1997 and a recession occurred around 2008.

For the EA case shown in Figure 4, one clear peak of *S-GAS rho* is in 2009:Q1, which corresponds to the economic shock from the collapse of Lehman Brothers on September 2008. The peak is steeper than in the Asia–Pacific case. Another two peaks are found in 2010:Q2 and 2011:Q1. These peaks correspond to the European sovereign debt crisis. This crisis took place from the end of 2009; it lasted until 2012. Therefore, we have another but weaker peak in 2012:Q4. These peaks are not clear for the Asia–Pacific case.

SAR-8 rho in EA shows a similar tendency, again. Actually, *CO* in EA shows a great recession in 2008. From this, recession stemming from the collapse of Lehman Brothers on September 2008 was more severe in EA than in the Asia–Pacific. A steeper peak in EA around 2008 is plausible. As might be apparent from the high business cycle correlation among EA countries in Table 4, business cycle synchronization is related to the degree of economic integration to some extent.

In either the Asia-Pacific or EA case, the value of *S-GAS rho* remains around zero when the *CO* value is around or over zero, i.e. the economic situation is not in a bad phase. Therefore, the business cycle is not synchronized in such a phase but is in divergence. The Great Moderation from the mid-1980s to 2007 is a period of calm volatility in macroeconomics, except for the Asian Financial Crisis in 1997.[12]

Therefore, common large shocks lead to prominently synchronized business cycles of countries closer to each other within the Asia-Pacific and EA. However, *S-GAS rho* settles down after economic crises. These facts indicate a different tendency from that found by Moneta and Rüffer (2009) who point out lasting effects after the economic crisis. Our main results are in line with that of Ductor and Leiva-Leon (2016). Their results show that after the Great Moderation period, synchronization increased to its peak at the end of 2008. They also point out that the phase of business cycle differs between European countries and emerging markets from other countries because of European debt crisis. Additionally, our results show that the short-term fluctuation is not clear in *SAR-8 rho*; *S-GAS rho* is useful for inspecting short horizons and movements per month.

4.2 Comparison between synchronization and volatility

Next, we verify the relations between estimated *S-GAS rho* and business cycle volatilities of Asia–Pacific and EA. The instantaneous volatility of business cycles is estimated with the GARCH (1, 1) model. The GARCH (p, q) model is described below as

$$y_t = \mu + \epsilon_t, \qquad (18)$$

$$\epsilon_t = \sigma_t z_t, \;\; \sigma_t > 0, \; z_t \sim N(0,\, 1), \quad (19)$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2, \qquad (20)$$

where y_t denotes the common GDP growth rate, as already estimated above, σ_t^2 represents instantaneous volatility of business cycle (*vol* hereafter). The estimation period is 1996:Q3 – 2017:Q4: the sample size is 86.

As a result, from Figures 5 and 6 in which *S-GAS rho* and *vol* are described, it is noteworthy that *S-GAS rho* and *vol* show considerably similar motions in the cases the Asia–Pacific or EA. Therefore, when economic shocks occurred and the business cycle volatility soars, business cycle synchronization will be similarly inflated.

Two cases are assumed for business cycle synchronization. For instance, presuming geographically or economically closer countries A, B, and C. The first case is that some exogenous economic shock will influence country A. Then, B and C are

[12] There are other exceptions. The crises in Mexico, Russia, and Brazil in 1994-95, 1998, and 1999, respectively.

contemporaneously affected by country A and mutually interact. The second case is that all countries (A, B, and C) might be affected by a common exogenous shock contemporaneously. A second case is that an exogenous common economic shock will contemporaneously but independently influence countries A, B, and C, and that they move in the same direction, i.e., growth rates will decrease at similar magnitudes simultaneously, without economic propagation among countries A, B, and C.

Selover et al. (1999) conclude that a major force underlying the international business cycle synchronization might be the "mode-locking" phenomenon. It refers to the situation when slight vibrations are transmitted from one clock to another, and this leads to the clocks oscillating at roughly the same frequency. Accordingly, in this study, we treat business cycle synchronization as a first case: there exists a propagation mechanism.

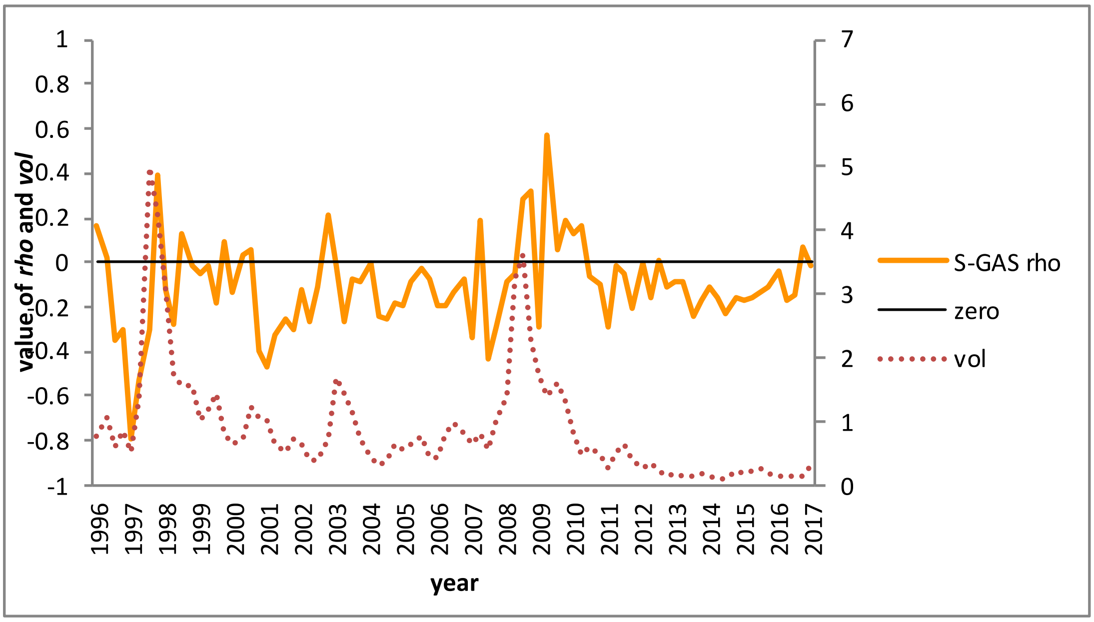

Figure 5 Estimated synchronization parameter with Spatial GAS model, and business cycle volatility of the Asia–Pacific

Note: *vol* is the estimated volatility of common business cycle movements in the Asia–Pacific using GARCH. Scale of *vol* is on the right side vertical axis.

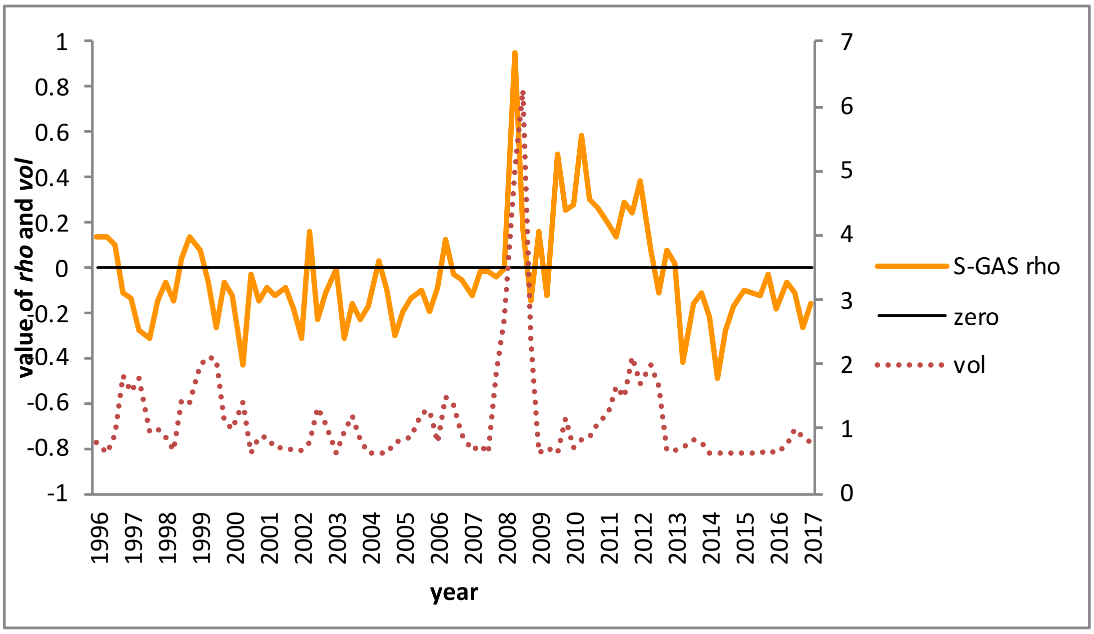

Figure 6 Estimated synchronization parameter with Spatial GAS model, and business cycle volatility of Euro Area

Note: *vol* is the estimated volatility of common business cycle movements in Euro Area using GARCH. The scale of *vol* is on the right-side vertical axis.

5 Conclusion

Instead of using structural analyses, in this study, we explore short time effects using one-step methodology. We apply space–time econometric methodology: spatial generalized autoregressive score model by Blasques et al. (2016) for measuring business cycle synchronization. We estimate a “spatial parameter” which denotes a “business cycle synchronization parameter.” Business cycle synchronization is defined as a parameter that is time-varying.

The estimated business cycle synchronization parameter show a high value during economic turmoil, such as the Asian crisis of 1997, the collapse of the dot-com bubble (or internet bubble), European sovereign debt crisis, and the collapse of Lehman Brothers in 2008.

Our finding is that when common business cycle movements show severe economic shocks, business cycle synchronization exhibits high values. In addition to this, when economic shocks occurred and business cycle volatility soared, business cycle synchronization is inflated similarly. Finally, based on our results, business cycle synchronization is related to some extent to the degree of economic integration.

With the recent increase in economic integration, exogenous shocks increase geographically and economically closer countries' business cycle synchronization to each other, and such shocks cause economic instability.

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