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## Estimating regional integration using the Bayesian state-space approach

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# ESTIMATING REGIONAL INTEGRATION USING THE BAYESIAN STATE-SPACE APPROACH

*Manuel Leonard Albis, Mara Claire Tayag, and Jong Woo Kang*

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## ABSTRACT

Estimating regional integration faces challenges because of incomplete data from missing values and insufficient time spans. A key advantage of a dynamic factor model estimated using the Bayesian state-space approach is its ability to handle missing values and aggregation of the regional integration indicators. This approach yields estimates of bilateral economic integration (BEI) using regional integration indicators on four dimensions: trade, foreign direct investments, finance, and migration. The regional integration index (RII) is derived by applying network density to the BEI estimates to represent the strength of regional integration within Asia and the Pacific. The BEI indexes not only serve to estimate the overall RII but enable the identification of economy pairs and dimensions that are driving regional integration in Asia and the Pacific. The estimated RII for Asia and the Pacific declined slightly in recent years, and the integration network became more centered around the People's Republic of China.

**Keywords:** Bayesian state-space model, network density, regional integration index

**JEL codes:** F02, F15, C8, C11

## 1. Introduction

Complete, comprehensive, and comparative regional integration indexes (RIIs) can play an important role in monitoring the progress in regional integration and deriving policy implications on regional cooperation. The success of targeted regional development programs and policies can depend on accurate assessment of a specific economy across different aspects of integration. However, estimating the degree of regional integration is no simple matter. The availability of numerous integration indicators, questions about how such indicators are aggregated, and incomplete data—resulting from missing values and inadequate timespans—are among factors that create challenges.

This paper, in acknowledging the complexities, aims to outline methods to generate regional integration measures at the economy-pair level. This can be used to create an RII describing the collective economic cohesiveness of all economies in Asia and the Pacific.<sup>1</sup>

A dynamic factor model estimated through the Bayesian state-space approach is used to generate indexes from several regional integration indicators of Asian economies. A key advantage of the approach is its ability to handle missing values and aggregation of regional integration indicators through its estimation procedure. This allows the model to run indefinitely without missing data until the results converge. Furthermore, because a full time-series is used to estimate the value of the indicator, the Bayesian state-space approach eliminates the requirement for missing data to be imputed or otherwise manipulated (Kim and Nelson 2001; Durbin and Koopman 2012).

This paradigm also has the benefit over the principal component analysis (PCA). PCA requires a data set with no missing values, and would entail preliminary missing value imputation, while missing value estimation is part of the Bayesian state-space estimation.

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<sup>1</sup> Asia and the Pacific, or Asia, consists of the 49 regional member economies of the Asian Development Bank (ADB). The composition of economies for Central Asia, East Asia, the Pacific and Oceania, South Asia, and Southeast Asia is outlined in: ADB. Asia Regional Integration Center. Economy Groupings. <https://aric.adb.org/integrationindicators/groupings>.

PCA also disregards the potential autoregressive nature of time series data, while this structure is inherent in a state space model.

The principal component analysis (PCA) is commonly used for calculating regional integration composite indexes. The Asian Development Bank (ADB) introduced the Asia-Pacific Regional Cooperation and Integration Index (ARCI), a comprehensive composite index that assesses regional integration across multiple dimensions (ADB 2021). This index allows for monitoring progress and identifying strengths and weaknesses at regional, subregional, and national levels.

Similarly, the Africa Regional Integration Index (ARII), a collaborative initiative involving the African Union Commission, United Nations Economic Commission for Africa, and the African Development Bank, provides users with comprehensive access to scores, rankings, and underlying data. The ARII covers various dimensions of regional integration, including trade, production networks, macroeconomy, infrastructure, and free movement of people.<sup>2</sup>

Furthermore, the Islamic Development Bank (IsDB) Integration Index serves as a composite measure involving five key dimensions of economic integration (IsDB 2022). These dimensions encompass trade and investment integration, financial markets integration, production networks, connectivity and logistics, and human mobility and institutional integration. The IsDB Integration Index offers a holistic perspective on economic integration, considering diverse aspects to provide a nuanced understanding of the integration landscape.

The Bayesian state-space approach has benefits over the PCA. PCA requires a data set with no missing values and would entail preliminary missing value imputation, while missing value estimation is part of the Bayesian state-space estimation. PCA also disregards the potential autoregressive nature of time series data, while this structure is inherent in a state-space model.

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<sup>2</sup> Africa Regional Integration Index. <https://www.integrate-africa.org/>.

Section 2 illustrates methodology and data. Section 3 discusses the analysis of results. Section 4 concludes with suggestions for future studies.

## 2. Methodology and Data

### 2.1. Degree of Integration Between Two Economies

Rayp and Standaert (2017) estimate the degree of integration between two economies using the dynamic factor model in state-space representation and this study follows their approach. The first step is to calculate the bilateral economic integration (BEI) for all economy pairs. The second step is to estimate an overall RII for Asia using all the estimated BEI indexes. The BEI for a particular economy-pair is estimated from a pool of integration indicators representing directed flows from one economy to another. This implies that two BEIs are extracted: (i) representing flows of economy A and B relative to the total flows of economy A, and (ii) representing flows of economy B and A relative to the total flows of economy B. This totals to  $p(p - 1)$  BEIs extracted, where  $p$  is the number of economies.

Let  $y_{it}^{(j)}$  be the  $j^{th}$  integration indicator  $j = 1, \dots, k$  for the  $i^{th}$  economy-pair  $i = 1, \dots, n$ , at time  $t = 1, \dots, T$ . The  $y_{it}^{(j)}$  can be expressed in a linear regression form, being explained by a constant term  $C^{(j)}$ , the integration index  $BEI_{it}$  with its corresponding coefficient  $Z^{(j)}$ . A random fluctuation  $\epsilon_{it}^{(j)}$ . Only  $y_{it}^{(j)}$  is observed and the regressor  $BEI_{it}$  is assumed to be a latent variable. Given a pool of  $k$  integration indicators  $y_{it}^{(j)}$ ,  $BEI_{it}$  is estimated using the dynamic factor model, given by:

$$y_{it}^{(j)} = C^{(j)} + Z^{(j)}BEI_{it} + \epsilon_{it}^{(j)} \quad (1)$$

where  $\epsilon_{it}^{(j)} \sim N(0, H^{(j)})$ ,  $Cov(\epsilon_{it}^{(j)}, \epsilon_{i^*t}^{(j^*)}) = 0$  for all  $i \neq i^*$  and  $j \neq j^*$ . The  $C^{(j)}$ ,  $Z^{(j)}$ , and  $H^{(j)}$  are parameters to estimate, one set for each  $j$ . The term in  $Z^{(j)}$  is called the factor loading of the BEI to the variable  $y_{it}^{(j)}$ . Equation 1 only includes a single factor or BEI. An extension



of this form is to extract multiple factors representing different dimensions of economic integration, at the cost of an increased number of parameters to estimate.

The equation for  $BEI_{it}$  is assumed to follow a Markovian structure and is given by:

$$EI_{it} = T^{(i)}BEI_{i,t-1} + v_{it} \quad (2)$$

where  $v_{it} \sim N(0,1)$ ,  $Cov(v_{it}, v_{i^*,t}) = 0$  for all  $i \neq i^*$ .  $T^{(i)}$  is an autoregressive parameter.  $BEI_{it}$  is initialized to 0 at  $t = 0$ ,  $BEI_{i,0} = 0$ . Combining Equation 1 across all  $i$  and  $j$  yields the measurement equation of a state space model, and combining Equation 2 across all  $i$  yields the state equation.

To facilitate the comparability of BEIs across economy-pairs and time, it is assumed that  $C$ ,  $Z$ , and  $H$  are fixed across  $i$  and  $t$ . A high BEI for the economy pair A and B, wherein the flows are scaled relative to the total flows of economy A, implies that economy B is important to economy A. The BEI is not commutative. It is possible that the BEI of A to B is high, but the BEI of economy B to A is low; a usual case then is where A is a small economy and economy B is larger. An increasing trend in the BEI of economy A to B implies the strengthening of economy A's integration with B.

### ***Bayesian State-Space Estimation of the Dynamic Factor Model***

The parameters of the model are estimated using the Bayesian approach. Each parameter is treated as random and given a prior distribution which represents the researcher's uncertainty about the true value of the parameter. The prior distributions are updated by applying the Bayes theorem to calculate the posterior distribution:

$$p(\boldsymbol{\theta}|\mathbf{X}) = \frac{L(\boldsymbol{\theta}|\mathbf{X})p(\boldsymbol{\theta})}{p(\mathbf{X})} \quad (3)$$

where  $p(\boldsymbol{\theta})$  is the prior distribution of the parameter vector  $\boldsymbol{\theta}$ ,  $L(\boldsymbol{\theta}|\mathbf{X})$  is the likelihood distribution given the observed data  $\mathbf{X}$ , and  $p(\mathbf{X})$  is the marginal likelihood, or the likelihood distribution integrating out the parameter  $\boldsymbol{\theta}$ . The number of model parameters

and latent values of *BEIs* are reported in Table 1. Bayesian estimation enables simultaneous estimation of both the model parameters and latent variables.

**Table 1. Parameter Counts**

Parameter	Count
$C$	44
$Z$	44
$H$	44
$T$	1,260
$AEI$	27,720
<b>Total</b>	<b>29,112</b>

Source: Authors' computations.

The prior distributions used in the Bayesian estimation are:

$$C^{(j)} \sim N(0, 1) \quad (4.1)$$

$$Z^{(j)} \sim \text{Gamma}(\text{shape} = 2, \text{scale} = 1/2) \quad (4.2)$$

$$H^{(j)} \sim \text{Gamma}(\text{shape} = 2, \text{scale} = 1/2) \quad (4.3)$$

$$T^{(i)} \sim \text{Uniform}(-1, 1) \quad (4.3)$$

The gamma prior is to restrict  $Z^{(j)}$  and the variances  $H^{(j)}$  to positive values. The uniform distribution for the autoregressive parameters  $T^{(i)}$  implicitly assumes a stationary  $BEI_{it}$  series. The *BEI* distributions are based on the specification of Equation 2.

Gibbs sampling (Geman and Geman 1984) is used to sample from the posterior distribution of the parameters. The procedure is a general Markov Chain Monte Carlo (MCMC) approach to estimating statistical models (Gelfand and Smith 1990; Gelfand 2000). The posterior sampling is simplified by partitioning the parameter  $\theta$  into  $r$  blocks  $\{\theta_1, \dots, \theta_r\}$ , and sampling is instead done per block, which is smaller in size than with the entire vector  $\theta$ . The parameter vector  $\theta$  is assumed to follow a Markovian process, wherein its current state  $\theta^{(l)}$  is dependent on the previous  $\theta^{(l-1)}$ . The Gibbs sampling starts by initializing the parameter vector  $\theta^{(0)} = \{\theta_1^{(0)}, \dots, \theta_r^{(0)}\}$ . To move from the current state  $\theta^{(l)}$  to  $\theta^{(l+1)}$ , samples are drawn starting from the conditional distribution of the first parameter block given the previous state  $\theta^{(l)}$ :

$$\boldsymbol{\theta}_1^{(l+1)} \sim p(\boldsymbol{\theta}_1 | \boldsymbol{\theta}_2^{(l)}, \dots, \boldsymbol{\theta}_r^{(l)}) \quad (5.1)$$

Samples are then drawn for the second parameter block from its conditional distribution, given the previous state  $\boldsymbol{\theta}^{(l)}$  with the updated  $\boldsymbol{\theta}_1^{(l+1)}$ :

$$\boldsymbol{\theta}_2^{(l+1)} \sim p(\boldsymbol{\theta}_2 | \boldsymbol{\theta}_1^{(l+1)}, \boldsymbol{\theta}_3^{(l)}, \dots, \boldsymbol{\theta}_r^{(l)}) \quad (5.2)$$

This is repeated until the last block is sampled from its conditional distribution given the latest states of the earlier blocks:

$$\boldsymbol{\theta}_r^{(l+1)} \sim p(\boldsymbol{\theta}_r | \boldsymbol{\theta}_1^{(l+1)}, \dots, \boldsymbol{\theta}_{r-1}^{(l+1)}) \quad (5.3)$$

Thus, the Gibbs iteration across the partitioned parameter vector produces the updated  $\boldsymbol{\theta}^{(l+1)}$ . The process is repeated several times as the limiting distribution of  $\boldsymbol{\theta}^{(l)}$  is the true posterior distribution of the parameter vector  $\boldsymbol{\theta}$ . Several sets of starting values for the parameters can be used to determine the robustness of results. Input of a different set of starting values produces a series of estimated parameters, which is called a chain. Convergence is achieved if the chains are observed as fluctuating around a common region along the real line, which is described as a high probability region for the true value of the parameter.

Gibbs sampling for the model is implemented using the JAGS program (Plummer 2003) in the R software using the R2jags package (Su and Yajima 2012). Ten chains were set for the Gibbs sampling, which was repeated for 30,000 iterations, with the first 20,000 discarded as burn-in.

The values of the parameters for the remaining 10,000 iterations are deemed to be the samples from the posterior distribution. The parameters are estimated by the posterior mean, which is operationalized by getting the average of the 10,000 samples from the posterior distribution. Moreover, with 10 chains, there will be 10 estimates of the posterior means for each parameter. The 10 chains produce similar regional integration values, showing a convergence of results. The final BEI estimates are the mean of the 10 chains.

The bilateral flow variables used in estimating the BEI are discussed in section 2.3. Moreover, Appendix A.1 shows the results of the parameter estimation.

## 2.2. Regional Integration Index

In estimating the RIIs, Rayp and Standaert (2017) used the network density to represent the strength of regional integration, which is defined as the number of strong bilateral connections relative to the number of potential connections. The economies are represented in a directed network to facilitate calculation of the network density. Each economy is treated as a node in the network, while the  $BEI_{it}$  is viewed as the edge. Bidirectional edges between two economies can be obtained, as indicated in section 2.1. This approach allows the calculation of a regional integration index across time.

In this study, a strong connection between two nodes exists if the BEI value is greater than the 80th percentile across years and across all economy pairs in the data set. This is facilitated by getting the empirical cumulative distribution of the BEI values across all years and economy-pairs. BEI values that are higher than the 80th percentile of the distribution are deemed strong connections.

The RII is then calculated using the percentage of strong connections relative to the total number of possible connections of a certain group or region. For example, in the case of Asia, there are 28 individual economies or groups in this analysis, which translates to 756 possible directional connections without loops.

## 2.3. Regional Integration Indicators

In this study, four categories of regional integration data are used: (i) trade, which is categorized into trade in manufactured goods, primary commodities, and services (transport, travel, other commercial services, and goods-related services); (ii) foreign direct investment (FDI); (iii) finance; and (iv) migration. All the indicators are bilateral or at economy-pair level. The trade in goods data are from the United Nations Commodity Trade Database (UN COMTRADE), which includes bilateral exports and imports

transactions, using the Standard International Trade Classification (SITC) by section (2 aggregations).<sup>3</sup> Trade in services data are from Balanced Trade in Services (BaTIS) data set (based on the Balance of Payments and International Investment Position Manual Sixth Edition or BPM6), compiled by the World Trade Organization (WTO)–Organisation for Economic Co-operation and Development (OECD), which include four services sector categories.<sup>4</sup> The balance of payments-based FDI data are from ADB’s Asian Economic Integration Report (AEIR) FDI Database.<sup>5</sup> Finance-related data include short-term and long-term portfolio investment in debt securities and equities from the Coordinated Portfolio Investment Survey (CPIS) of the International Monetary Fund (IMF). Migration data are from the UN International Migrant Stock.

The regional integration indicators are computed by normalizing the bilateral data to reflect the relative importance of the directional flow using (i) the nominal gross domestic product (GDP) or total population of the reporting economy, and (ii) total flows. Incoming (outgoing) flows are normalized using the total incoming (outgoing) flows for the reporter economy A and partner economy B, at time  $t$ , given by:

$$Total\ Incoming\ Flows_{A,t} = \sum_B Incoming\ Flows_{B,t} \quad (6.1)$$

$$Total\ Outgoing\ Flows_{A,t} = \sum_B Outgoing\ Flows_{B,t} \quad (6.2)$$

Export data are converted into shares relative to total outflows (exports) of the reporting economy, while import data are converted relative to total inflows (imports) of the reporting economy. Both export and import indicators are also normalized relative to the GDP of the reporting economy. Finance-related data are also normalized using the GDP and total flows of the reporting economy. Migration indicators are normalized by total population and total migration flows of the reporting economy. GDP and population data

<sup>3</sup> The two SITC aggregations are (i) primary commodities, except nonferrous metals; and (ii) manufactured goods, precious stones, nonferrous base metals.

<sup>4</sup> The four service categories are (i) transport, (ii) travel, (iii) goods-related services, and (iv) other commercial services.

<sup>5</sup> For a more detailed description of the data, see online Annex 1 of AEIR 2018: [http://aric.adb.org/pdf/aeir2018\\_onlineannex1.pdf](http://aric.adb.org/pdf/aeir2018_onlineannex1.pdf).

are from the IMF's World Economic Outlook and World Bank's World Development Indicators and data sets. In total, 44 standardized regional integration indicators are included in the analysis (Appendix A.2).

## 2.4. Bilateral Economy-Pairs

Economies are selected primarily based on data availability, which means that economies without GDP, total inflows, and outflows are excluded from the sample as reporter and partner economies. Economies with insufficient GDP data are reported in Appendix A.3, while economies with insufficient total flows are in Appendix A.4. The global GDP after dropping 49 economies (\$95.3 trillion) is 99.5% of the original global GDP (\$95.8 trillion); and the global population (7.5 billion) is 95.4% of the original global population (7.9 billion), as shown in Table 2.

**Table 2: Global GDP and Population Before and After Exclusion of 49 Economies**

Year	Before dropping economies ( $N_0 = 218$ )		After dropping economies ( $N_1 = 169$ )	
	GDP (current, \$ million)	Population (million)	GDP (current, \$ million)	Population (million)
2000	33,803,811	6,143	33,375,216	5,914
2005	47,751,320	6,553	47,086,507	6,293
2010	66,572,442	6,970	65,347,866	6,678
2015	74,895,554	7,405	74,180,789	7,083
2020	84,698,927	7,821	84,045,668	7,467
2021	95,782,643	7,888	95,327,071	7,528

GDP = gross domestic product,  $N_0$  = initial number of economies,  $N_1$  = number of economies after excluding 49 economies.

Source: International Monetary Fund. World Economic Outlook October 2022 Database. <https://www.imf.org/en/Publications/WEO/weo-database/2022/October> (29 November 2022); and World Bank. World Development Indicators. <https://databank.worldbank.org/source/world-development-indicators> (29 November 2022).

Using the 169 individual economies in the analysis drastically increases the number of parameters and  $RI_t$ s to estimate. Recall that the number of economy-couples is  $n = p(p - 1)$ , where  $p$  is the number of economies. Thus,  $\mathbf{RI}_t$  and  $\mathbf{T}$  each have  $p(p - 1)$  elements. For a 169-economy data set,  $n$  is equal to 28,392 directional economy-pairs. Creating subgroups for the economies reduces the computational resources required in the analysis. Table 3 shows the individual economies and grouped economies in the analysis. The Central Asian subregion has four retained individual economies, East Asia and Southeast Asia each have six, South Asia has four, and the Pacific and Oceania have two each. The United States, Canada, Mexico, and the United Kingdom are retained as individual economies. Economies in Africa, the European Union (EU), and Latin America are given their own groups.

**Table 3: List of Economies and Groups**

Regions/Subregions	Individual Economy (retained)	“All Others” (aggregated)
Central Asia (8)	Azerbaijan	Armenia
	Kazakhstan	Georgia
	Kyrgyz Republic	Tajikistan
	Uzbekistan	Turkmenistan [dropped]
East Asia (6)	Hong Kong, China	
	Japan	
	Mongolia	
	People’s Republic of China	
	Republic of Korea	
	Taipei, China	
Southeast Asia (10)	Indonesia	Brunei Darussalam
	Malaysia	Cambodia
	Philippines	Lao People’s Democratic Republic
	Singapore	Timor-Leste [dropped]
	Thailand	
	Viet Nam	
South Asia (8)	Bangladesh	Bhutan
	India	Maldives
	Pakistan	Nepal
	Sri Lanka	
Pacific (14)	Papua New Guinea	Cook Islands [dropped]
	Fiji	Federated States of Micronesia [dropped]
		Kiribati
		Marshall Islands [dropped]
		Nauru [dropped]

*Continued of the next page*

Regions/Subregions	Individual Economy (retained)	“All Others” (aggregated)
		Niue [dropped]
		Palau [dropped]
		Samoa
		Solomon Islands
		Tonga
		Tuvalu
		Vanuatu
Oceania (2)	Australia	
	New Zealand	
Non-Asia	United States	Africa (47 economies)
	Canada	European Union (27 economies)
	Mexico	Latin America (30 economies)
	United Kingdom	Rest of the world (21 economies)

Source: Authors' compilation.

The number of economies after grouping the small economies while retaining the larger ones is equal to 36. This brings the number of directional pairs down to 1,260. The time horizon for the study is from 2000 to 2021, equivalent to 22 time points.

### 3. Results

#### 3.1. Bilateral Economic Integration Index

Table 4 displays the top 10 pairs of Asian economies with the highest bilateral economic integration (BEI) index for both 2000 and 2021. A higher BEI indicates greater integration of the reporting economy with the partner economy. The index also represents the significance of the partner economy's cross-border flows to the reporting economy relative to the latter's total flows (and GDP, if applicable).

In 2000, the Hong Kong, China–to–People's Republic of China (PRC) pair had the highest BEI index among all bilateral pairs in Asia, followed by New Zealand–Australia and Fiji–Australia. Key partners for cross-border flows for Asian economies included Australia, Japan, and the PRC.

In 2021, Hong Kong, China–PRC still held the strongest economic integration among Asian economy pairs. Mongolia–PRC in East Asia, Papua New Guinea–Australia in the Pacific and Oceania, and Malaysia–Singapore in Southeast Asia also remained at the top



10 list. These three economy pairs are discussed in detail below to provide examples of how the computed BEI indexes are interpreted and analyzed.

**Table 4: Bilateral Economic Integration Index—Top Economy Pairs Within Asia and the Pacific**

**(a) 2000**

Rank	Reporter	Partner	Value
1	Hong Kong, China	PRC	326
2	New Zealand	Australia	235
3	Fiji	Australia	234
4	Papua New Guinea	Australia	233
5	South Asia Group	India	223
6	Mongolia	PRC	220
7	Malaysia	Singapore	197
8	PRC	Hong Kong, China	194
9	Taipei, China	Japan	190
10	Thailand	Japan	188

**(b) 2021**

Rank	Reporter	Partner	Value
1	Hong Kong, China	PRC	660
2	South Asia Group	India	382
3	Mongolia	PRC	346
4	Papua New Guinea	Australia	285
5	Viet Nam	PRC	242
6	New Zealand	Australia	224
7	Singapore	PRC	221
8	Taipei, China	PRC	218
9	Malaysia	Singapore	216
10	Southeast Asia Group	PRC	214

PRC = People's Republic of China; South Asia Group = Bhutan, Maldives, and Nepal; Southeast Asia Group = Brunei Darussalam, Cambodia, and Lao People's Democratic Republic.

Source: Authors' estimates.

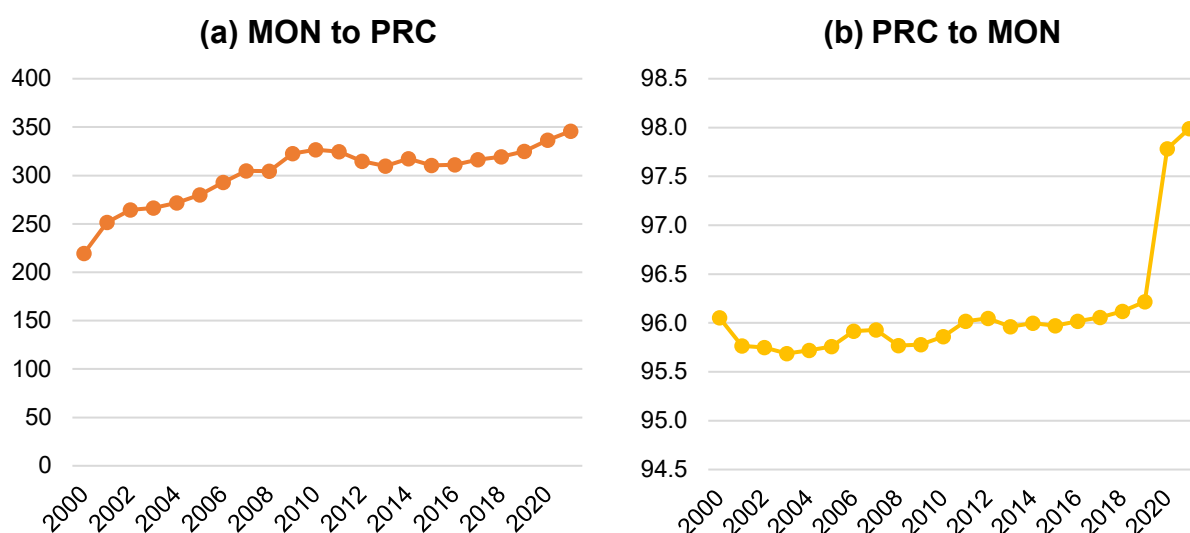
***Bilateral Economic Integration Index Estimates for Selected Economy Pairs***

Figure 1 illustrates the BEI index between the People's Republic of China (PRC) and Mongolia from 2000 to 2021. Notably, there was a rising trend in the BEI of Mongolia to the PRC from 2000 to 2010 (Figure 1a). Subsequently, the measure exhibited a steady decline until 2015 but has since been on an uptrend. The recent increase is primarily

attributed to Mongolia's reliance on primary commodity exports to the PRC and manufactured goods imports from the PRC, relative to its GDP.

Figure 1b, on the other hand, presents the BEI of the PRC to Mongolia. The index remained generally stable, hovering around 96 from 2000 to 2019, before it rose sharply during the coronavirus disease (COVID-19) pandemic. The sudden increase in the PRC's FDI outflows to Mongolia in 2020 may have explained this trend. It is also notable that the BEI estimates of Mongolia to the PRC (220 to almost 350) are higher than the BEI of the PRC to Mongolia (95–98), indicating that PRC flows are more important for Mongolia than the other way around.

**Figure 1: Bilateral Economic Integration Index Between the People's Republic of China and Mongolia**



MON = Mongolia, PRC = People's Republic of China.

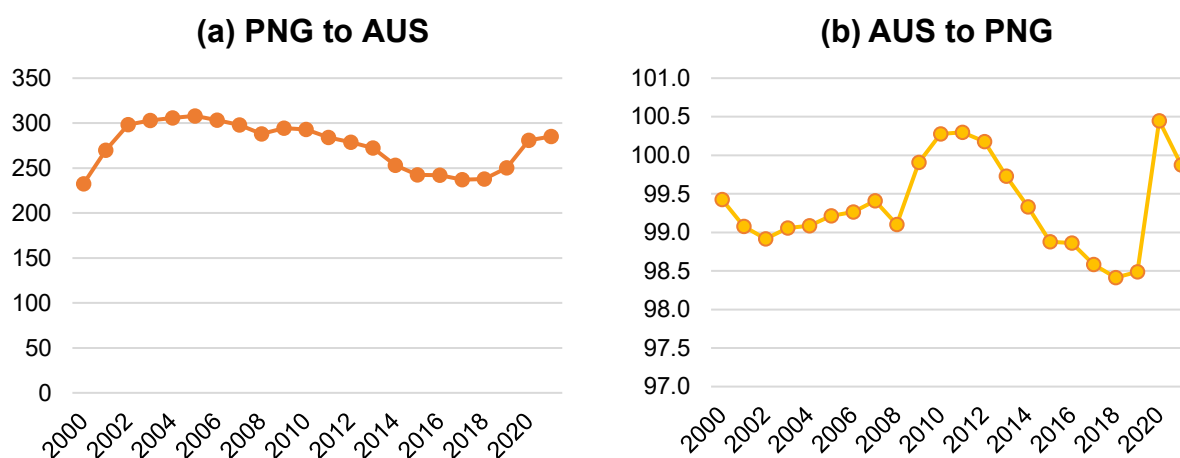
Source: Authors' estimates.

Figure 2 shows the BEI between Australia and Papua New Guinea. In the Pacific and Oceania subregion, this economy pair exhibited the strongest economic linkage, as indicated by the estimated BEI values in 2021 (refer to Table 4). Notably, there was an increase in the BEI indexes for both economies during the pandemic years, reversing the previous downward trend. However, the shift is more pronounced for the Australia-to-Papua New Guinea BEI (Figures 2a, 2b).

The increase in the BEI during the pandemic years is mainly attributed to the surge in BOP-based FDI that Papua New Guinea received from Australia. For the Australia–

Papua New Guinea BEI, the main factor is Australia's FDI outflows to Papua New Guinea, both as a percentage of Australia's total FDI outflows and as a percentage of its GDP. As expected, the cross-border flows of the larger economy (Australia) tend to be more important to the smaller one (Papua New Guinea) than the other way around.

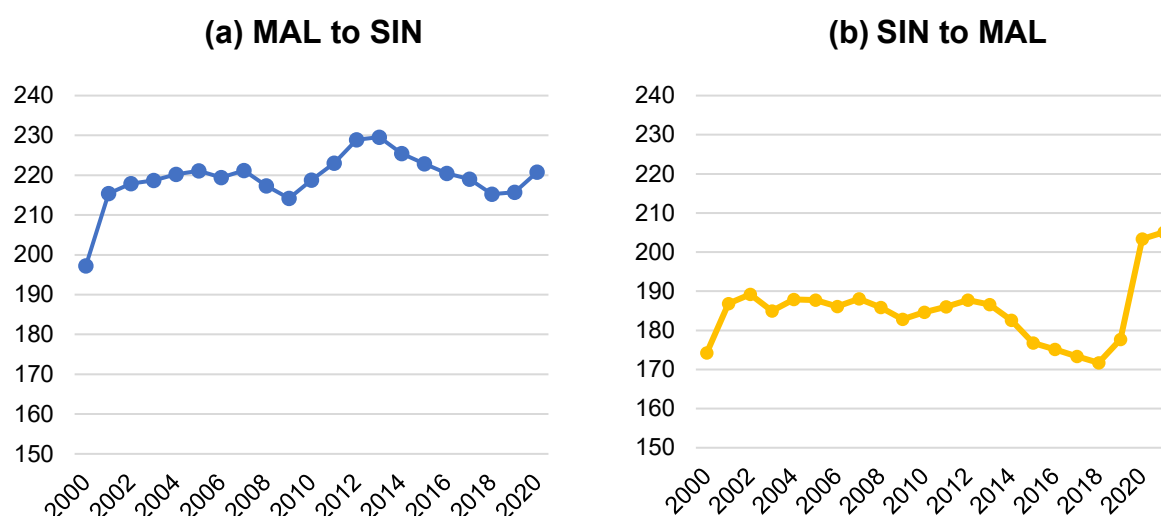
**Figure 2: Bilateral Economic Integration Index Between Australia and Papua New Guinea**



AUS = Australia, PNG = Papua New Guinea.

Source: Authors' estimates.

Figure 3 shows the BEI between Malaysia and Singapore, which posted the strongest cross-border flow linkage within Southeast Asia in 2021. The BEI values between Malaysia and Singapore are closely aligned, implying nearly the same degree of integration between the two economies. However, it is noteworthy that the BEI of Singapore to Malaysia rose more sharply during the pandemic years than that of Malaysia to Singapore. FDI outflows as share of the reporter's GDP is the main driver of integration between the two economies.

**Figure 3: Bilateral Economic Integration Index Between Malaysia and Singapore**

MAL = Malaysia, SIN = Singapore.

Source: Authors' estimates.

### ***Integration Trends of the PRC and Japan***

Another notable observation from the top 10 Asian economy pairs with the highest BEI in Table 4 is the rise in the number of Asian economies having the strongest linkage with the PRC—from 2 in 2000 to 6 in 2021. In contrast, this number declined for Japan. To delve deeper into the integration trends of these two economies, the top 10 economies worldwide that are strongly linked with them as reporting and partner economies are discussed in the succeeding paragraphs.

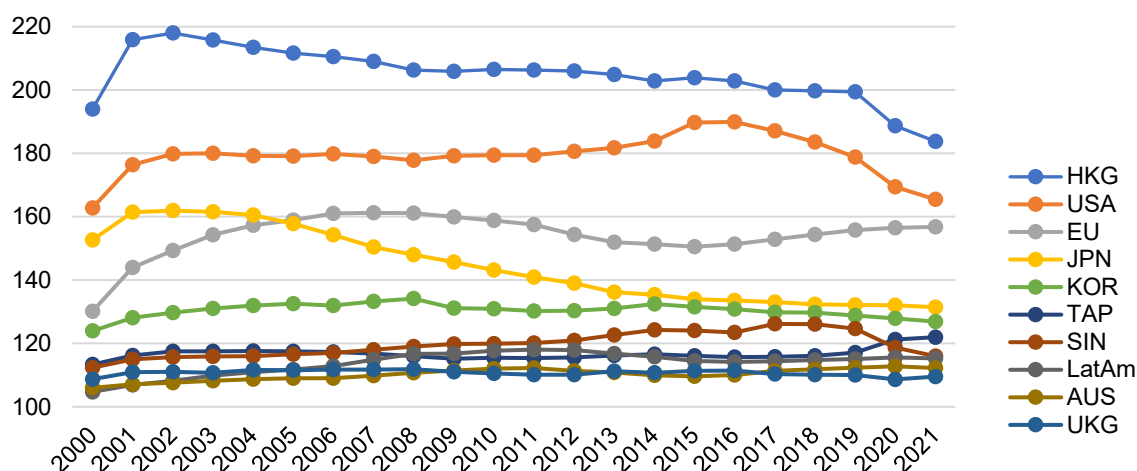
For the PRC, the most important partner economies include Hong Kong, China; the US; the European Union (EU); Japan; and the Republic of Korea (Figure 4a). The BEI of the PRC with these top 10 partners has been declining in recent years, except for the EU and Taipei, China, where the PRC's trade of manufactured goods has been on the rise. The BEI with the US increased until 2015 but gradually decreased until 2021, driven by the PRC's long-term debt securities investments and exports of manufactured goods to the US. The BEI with Japan has been decreasing, although the pace of decrease has slowed recently, as the PRC's manufactured goods imports from Japan weakened.

The top 10 economies most reliant on the PRC as their cross-border flow partner are predominantly from Asia, particularly from East Asia (Hong Kong, China; Mongolia; and Taipei, China) and Southeast Asia (Singapore, Viet Nam, and smaller economy group of Brunei Darussalam, Cambodia, and Lao People's Democratic Republic) (Figure 4b). With

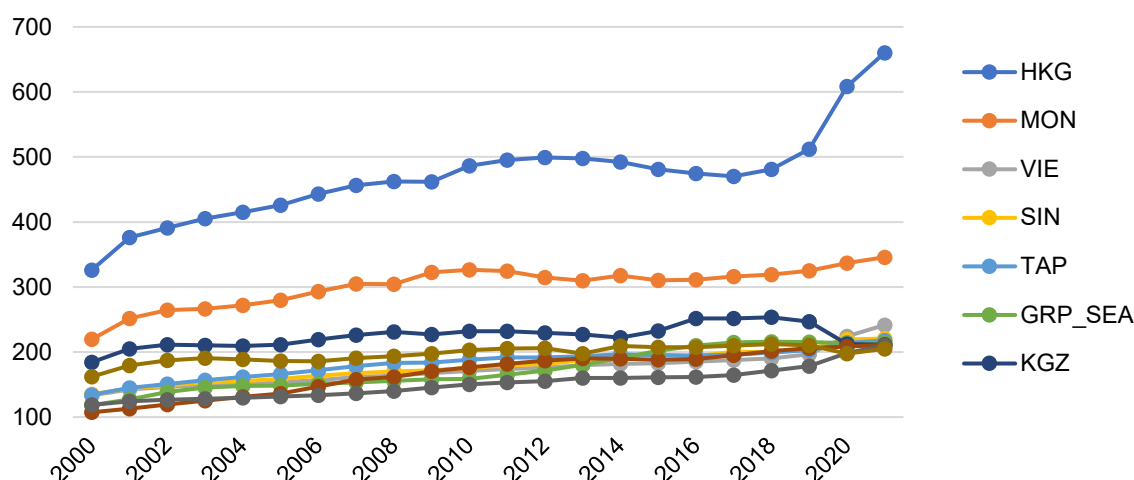
the exception of the Kyrgyz Republic, the BEIs of these economies with the PRC have been increasing since 2000, driven by improvements in their trade of manufacture goods and/or primary commodities with the PRC.

**Figure 4: Bilateral Economic Integration Index: PRC's Integration with Other Economies**

**(a) PRC as Reporter**



**(b) PRC as Partner**



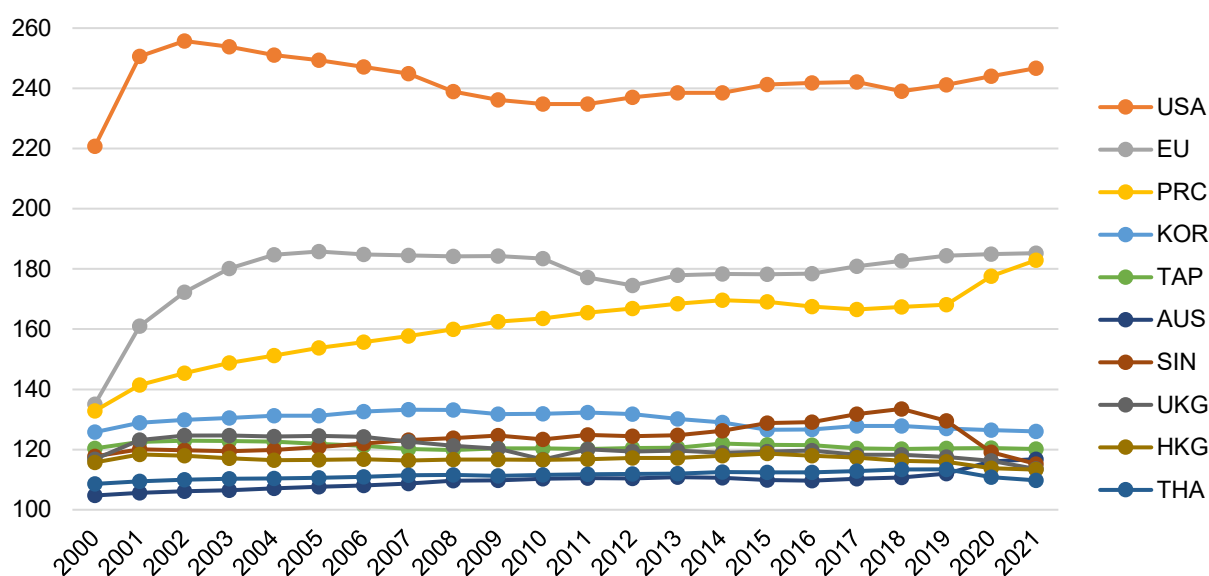
AUS = Australia; EU = European Union; GDP\_PAC = Pacific economy group (Kiribati, Samoa, Solomon Islands, Tonga, Tuvalu, Vanuatu); GRP\_SEA = Southeast Asia economy group (Brunei Darussalam, Cambodia, and Lao People's Democratic Republic); HKG = Hong Kong, China; JPN= Japan; KAZ = Kazakhstan; KGZ = Kyrgyz Republic; KOR = Republic of Korea; LatAm = Latin America; MON = Mongolia; PRC = People's Republic of China; SIN = Singapore; TAP = Taipei, China; UKG = United Kingdom; USA = United States; VIE = Viet Nam.

Source: Authors' estimates.

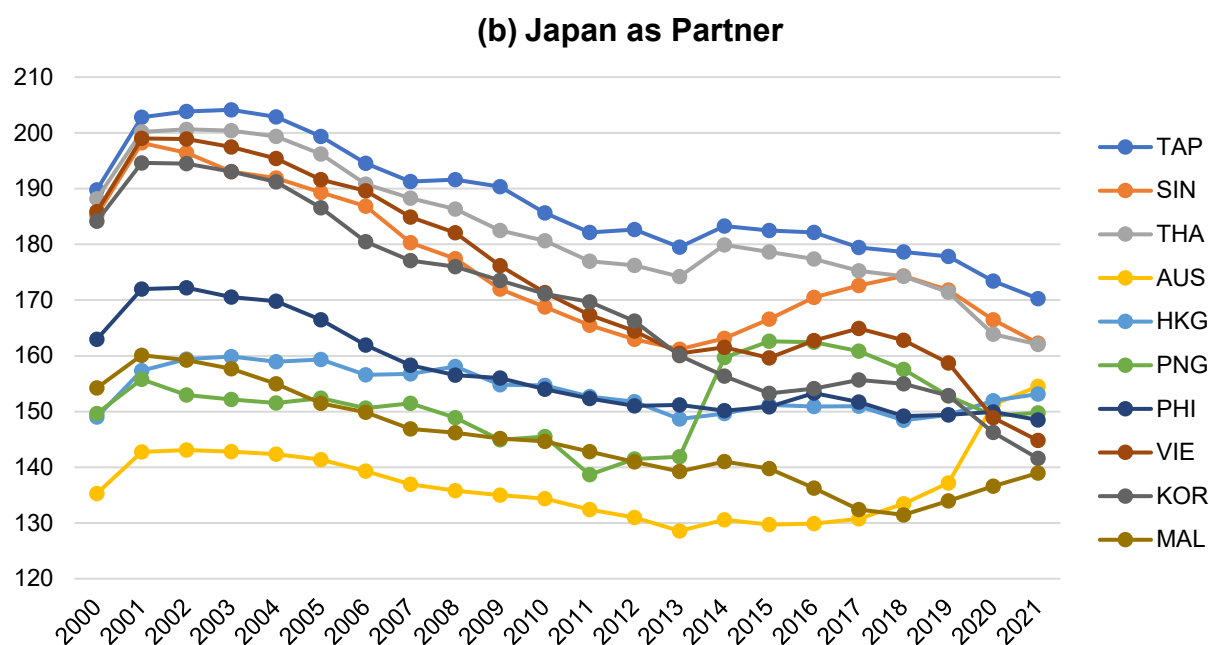
Japan's primary partners, ranked in order of importance, include the US, the EU, and the PRC (Figure 5a). The BEI index of Japan to these three economies has been increasing, particularly during the pandemic. Japan's outward portfolio debt and equity investment has been the driving factor for the heightened BEI to the US and Japan, while its imports of manufactured goods play a pivotal role in the increased integration with the PRC. The rest of Japan's top 10 partners are predominantly from Asia, with the exception of the UK.

Despite Japan's major partners being largely outside of Asia, the economies with the top 10 highest BEI to Japan are exclusively from Asia (Figure 5b). Based on the latest BEIs, Taipei, China ranks first on the list, followed by Singapore and Thailand. The BEIs of these economies to Japan have been steadily decreasing over the review period. Singapore's BEI was on a downtrend until 2013, experienced a sharp increase thereafter, peaked in 2018, and subsequently declined throughout the pandemic years. The main drivers of integration with Japan were inward portfolio debt investment for Taipei, China; outward portfolio equity and debt investment for Singapore; and exports and imports of manufactured goods for Thailand.

**Figure 5: Bilateral Economic Integration Index: Japan's Integration with Other Economies**  
(a) Japan as Reporter



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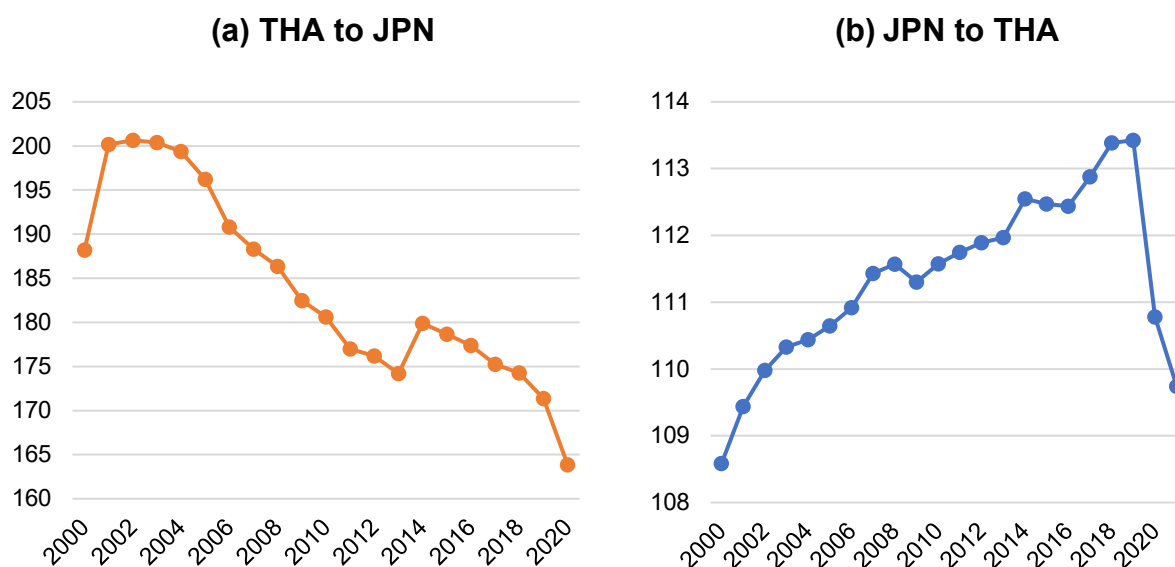
AUS = Australia; EU = European Union; HKG = Hong Kong, China; KOR = Republic of Korea; MAL = Malaysia; PHI = Philippines; PNG = Papua New Guinea; PRC = People's Republic of China; SIN = Singapore; TAP = Taipei, China; THA = Thailand; UKG = United Kingdom; USA = United States; VIE = Viet Nam.

Source: Authors' estimates.

### ***Dimensional Bilateral Economic Integration Index***

To determine the primary drivers behind the overall BEI, the study used the Bayesian state-space approach to estimate the dimensional BEI indexes for trade, FDI, finance, and migration. Given the substantial computational resources required for such an analysis across all economy-pairs, the estimation started with a single economy-pair. The Thailand–Japan pair was chosen because of its relatively more comprehensive bilateral data. It would also be interesting to know the factors behind the divergent trends observed in the BEI of Thailand to Japan and that of Japan to Thailand.

Examining the BEI trends between Thailand and Japan provides valuable insights. The BEI of Thailand to Japan, which was among the highest in Asia in early 2000s, experienced a sharp decline throughout the study period, with notable upticks in 2001 and 2014 (Figure 6a). Conversely, the BEI of Japan to Thailand exhibited a steady increase until 2018, reached a plateau in 2019, and underwent a sudden decline during the pandemic years (Figure 6b).

**Figure 6: Bilateral Economic Integration Index Between Japan and Thailand**

JPN = Japan, THA = Thailand.

Source: Authors' estimates.

The dimensional BEI indexes between Japan and Thailand are shown in Figure 7. The BEI of Thailand to Japan, reflecting the importance of Japan to Thailand, was primarily influenced by trade until 2013, shifted to FDI from 2014 to 2018, and then by finance during the pandemic years (Figure 7a). There was a notable decline in trade and an increase in FDI, indicating a substitution effect between these two dimensions until around 2016. The finance BEI increased sharply in 2015–2016—mostly because of the significant rise in short-term debt securities investment from Japan—and has remained relatively stable since. Migration consistently recorded the lowest values throughout the review period.

On the other hand, the linkages from Japan to Thailand remained generally stable across the period and for all the integration dimensions (Figure 7b). Migration consistently held the highest value, except in 2021, followed by trade and finance, with FDI consistently registering the lowest values. Understanding these dynamics sheds light on the patterns and factors influencing economic integration between Japan and Thailand.

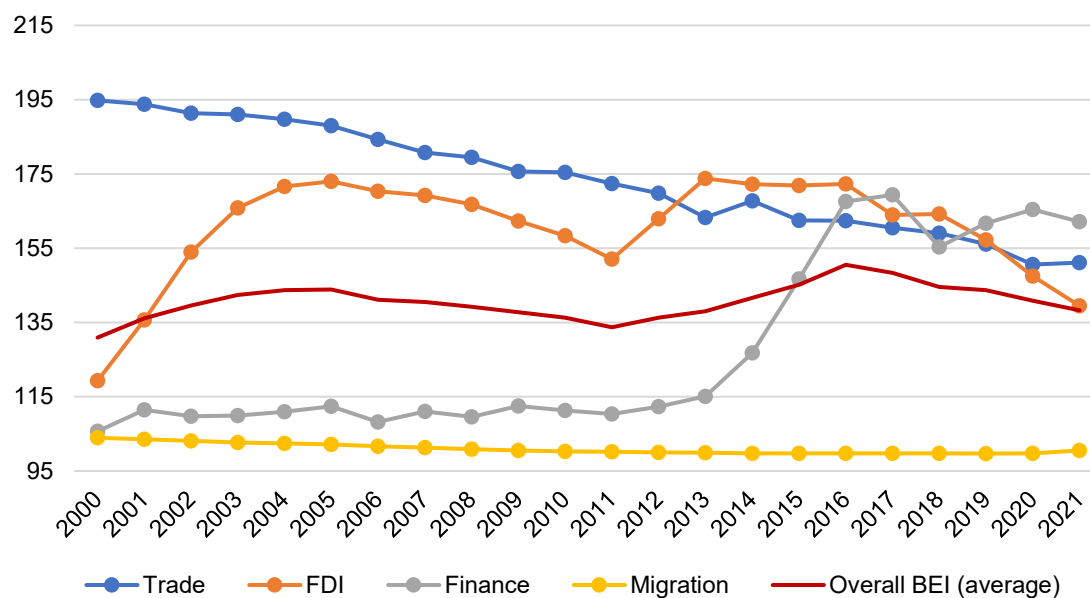
For robustness check, the dimensional BEI indexes were averaged to calculate the overall BEI index. This averaged index was subsequently compared with the original overall BEI index presented in Figure 6. The findings, illustrated in Figure 8, reveal that the trends for the average overall index and the original estimates are somewhat similar,



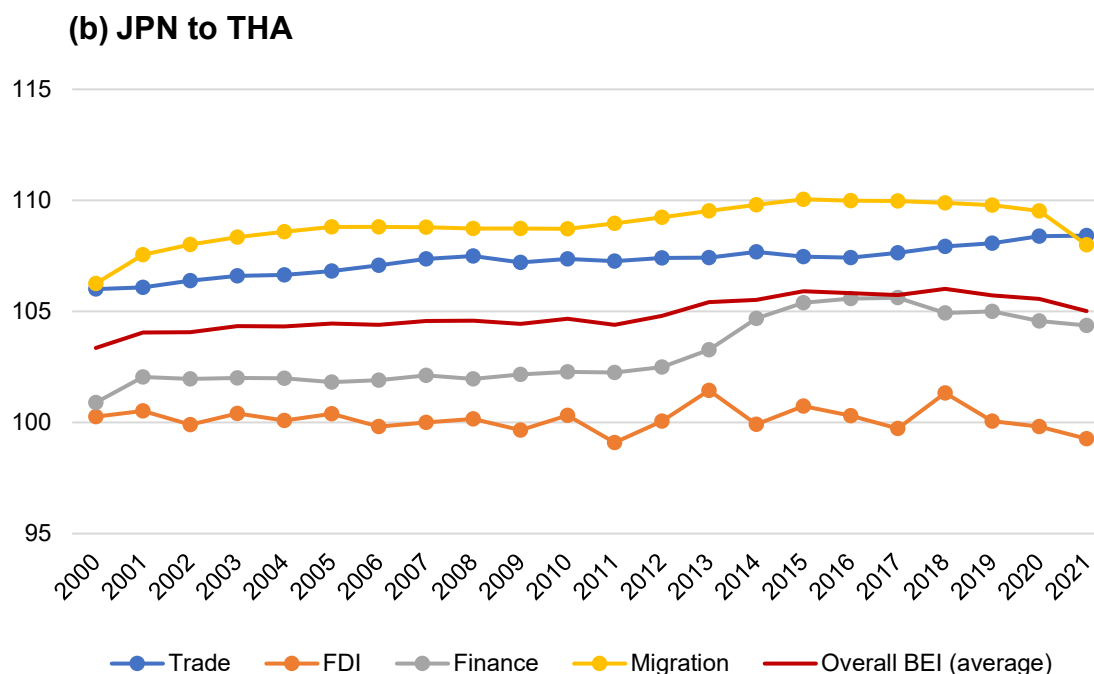
although the fluctuations in the original estimates were a bit more pronounced. These results contribute to the validation of the observed patterns of economic integration.

**Figure 7: Dimensional Bilateral Economic Integration Index  
Between Japan and Thailand**

**(a) THA to JPN**



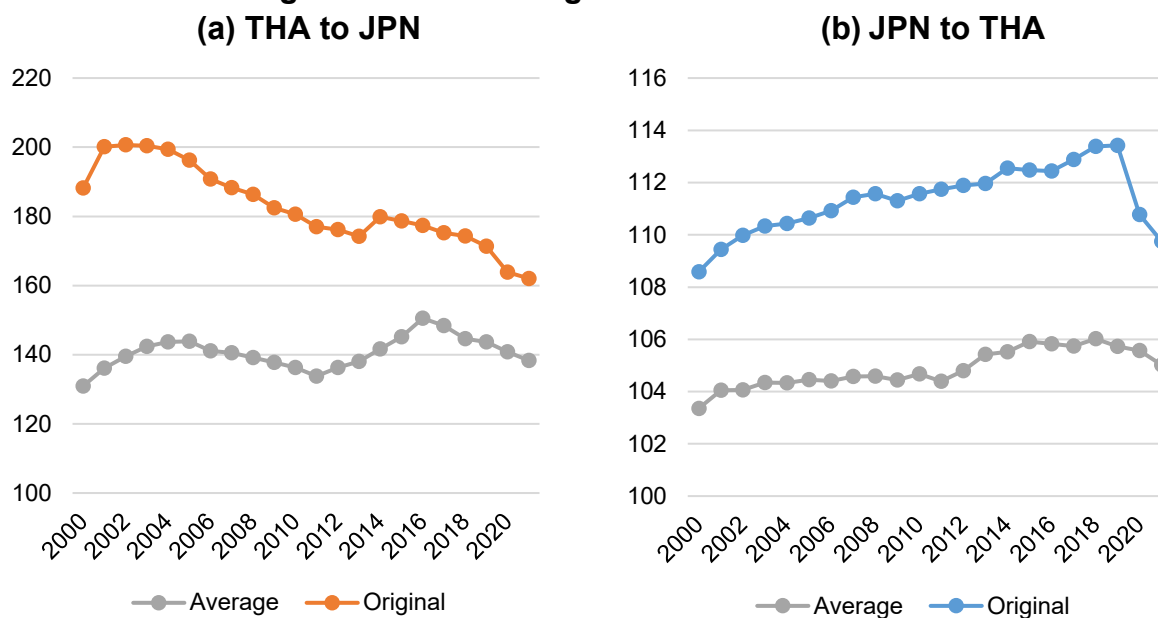
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BEI = bilateral economic integration, JPN = Japan, THA = Thailand.

Source: Authors' estimates.

**Figure 8: Overall Bilateral Economic Integration Index:  
Original versus Average of Dimensional Indexes**



JPN = Japan, THA = Thailand.

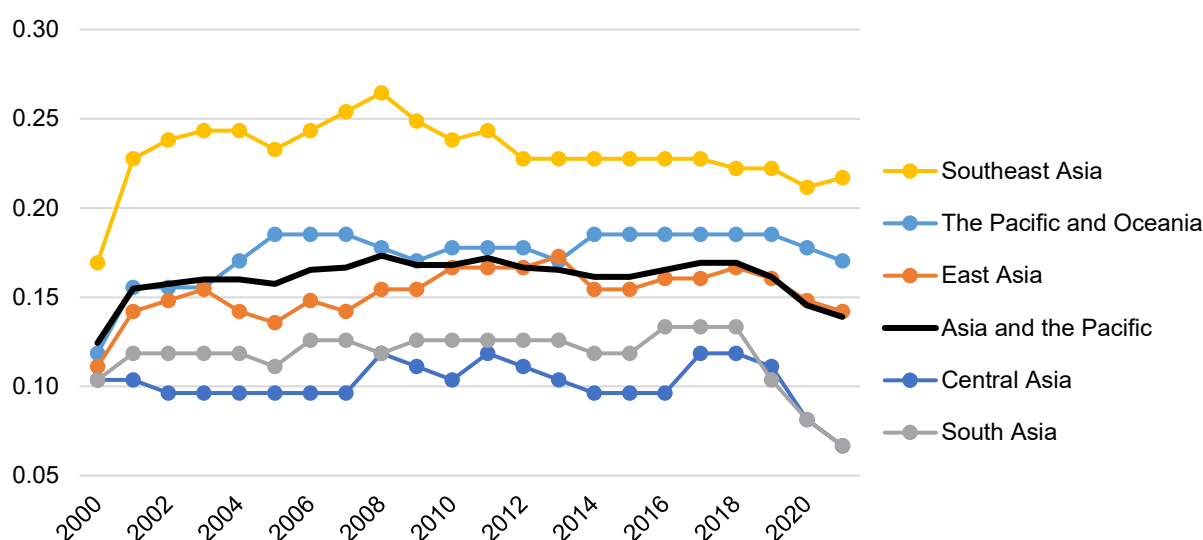
Source: Authors' estimates.

### 3.2. Regional Integration Index

In Figure 9, regional integration index (RII) for Asia is presented, calculated as the ratio of the number of strong bilateral connections (or high BEI indexes at the 80<sup>th</sup> percentile cutoff) to the number of all possible bilateral connections. The estimates indicate a significant increase in Asia's RII, rising from 0.124 in 2000 to a peak of 0.173 in 2008. From 2008 to 2018, the index remained relatively stable, hovering around 0.16–0.17. However, a noticeable and sudden decline started in 2019 with the onset of the COVID-19 pandemic.

When examined by subregion, Southeast Asia consistently exhibited the highest integration with Asia, followed by the Pacific and Oceania, and East Asia. In contrast, Central Asia and South Asia recorded the lowest integration index. During the pandemic years, all Asian subregions experienced a decline in their RII, except for a slight increase in 2021 for Southeast Asia. The most rapid decline occurred in Central Asia and South Asia.

**Figure 9: Regional Integration Index of Asia and the Pacific, by Subregion**



Note: Each subregion's RII estimates measures the subregion's integration with the whole of Asia and the Pacific.

Source: Authors' estimates.

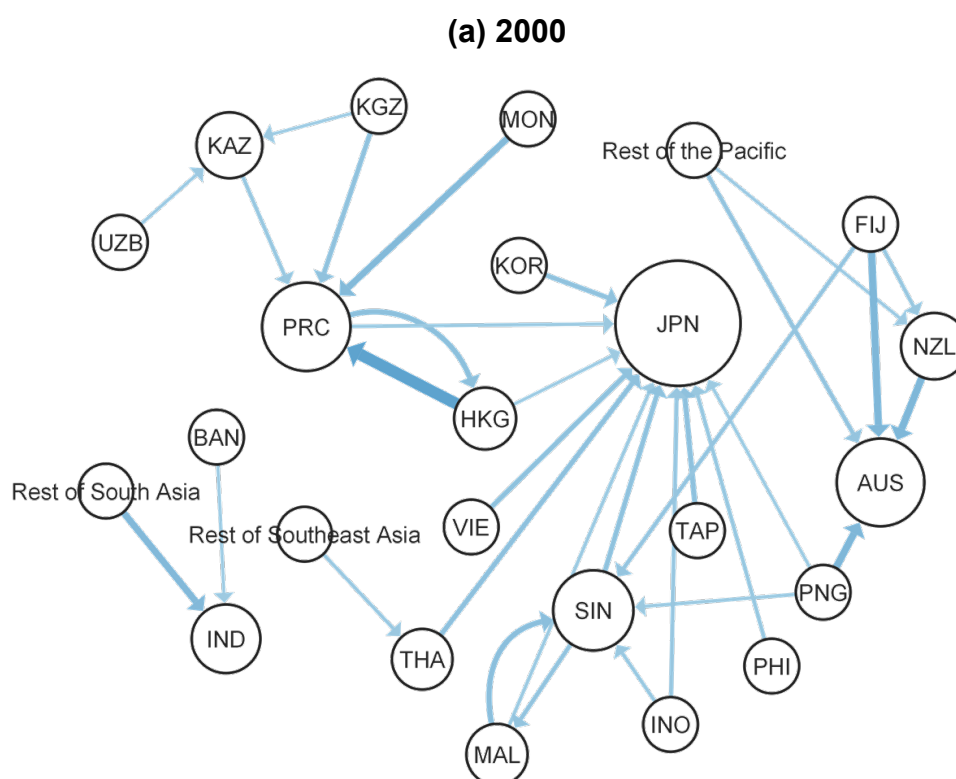
Figure 10 shows the network graphs for Asia based on the 80th percentile cutoff. The node size in the graphs corresponds to the weighted in-degree, representing the weighted average of the number of edges or arrows pointing to the node. The size and color

intensity of the arrows correspond to the directional BEI values; thicker arrows and more intense colors indicate higher BEI.

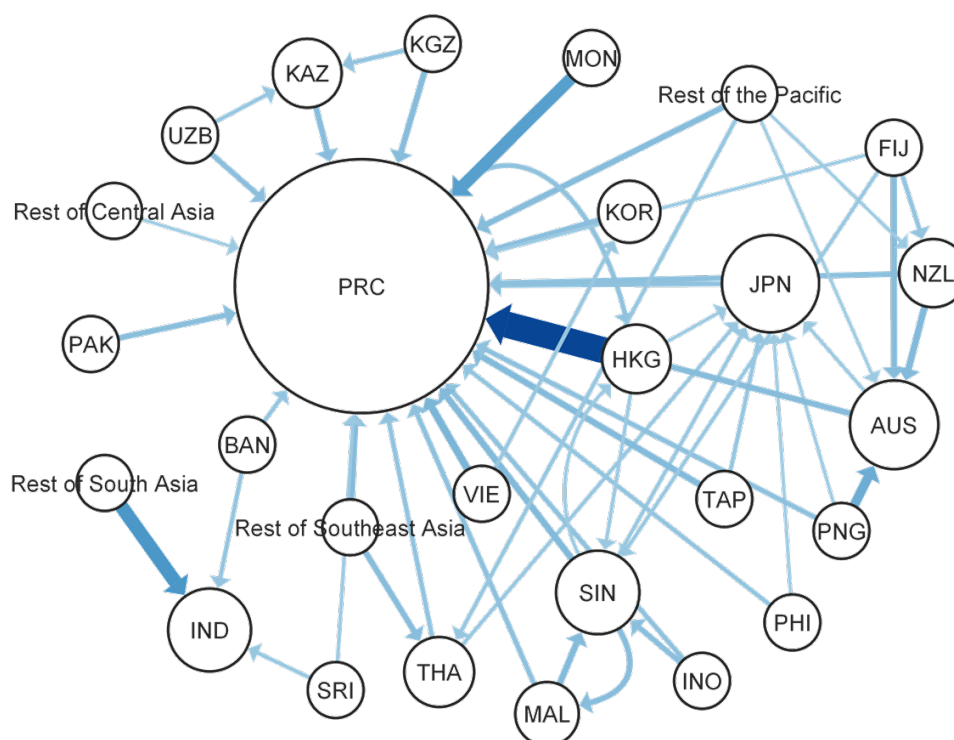
In 2000, several Asian economies had high integration with the PRC, Japan, Singapore, and Australia. Clusters can also be observed for South Asia, the Pacific and Oceania, and Southeast Asia (Figure 10a). Generally, Asia was most centered around Japan in 2000. Moving to 2021, the subregional clusters are still observable, but the network is more centered around the PRC (Figure 10b).

Appendix A.5 lists economies with more than three strong in-degree bilateral connections, where the RII is calculated by the percentage of strong bilateral connections following the 80th percentile cutoff relative to the number of all possible inbound connections,  $(p - 1)$ . In the early 2000s, Japan held the highest rank in terms of the number of inbound strong connections, while the PRC ranked third. The strong inbound connections to the PRC rapidly increased, equaling those of Japan by 2004. Subsequently, the strong inbound connections to Japan declined from 11 in 2006 to 7 in 2021.

**Figure 10: Network Graph of Asia's Regional Integration Links**



(b) 2021



AUS = Australia; AZE = Azerbaijan; BAN = Bangladesh; PRC = People's Republic of China; FIJ = Fiji; HKG = Hong Kong, China; IND = India; INO = Indonesia; JPN = Japan; KAZ = Kazakhstan; KOR = Republic of Korea; KGZ = Kyrgyz Republic; MAL = Malaysia; MON = Mongolia; NZL = New Zealand; Other CA = other Central Asia; Other PAC = other Pacific; Other SA = other South Asia; Other SEA = other Southeast Asia; PAK = Pakistan; PHI = Philippines; PNG = Papua New Guinea; SIN = Singapore; SRI = Sri Lanka; TAP = Taipei, China; THA = Thailand; UZB = Uzbekistan; VIE = Viet Nam.

Source: Authors' estimates.

#### 4. CONCLUSION AND WAYS FORWARD

The measurement of regional integration encounters challenges because of incomplete data stemming from missing values and insufficient time spans. To address these issues, this study used a dynamic factor model using the Bayesian state-space approach. In contrast to principal component analysis (PCA), the Bayesian state-space approach inherently addresses missing values, eliminating the need for preliminary imputation. Additionally, it considers the autoregressive nature of time series data, which the PCA may disregard.

The approach used in the paper not only addresses computational challenges but also yields indexes that offer insights into the evolving landscape of regional integration in

Asia. The BEI indexes not only serve to estimate the overall RII but also facilitate the identification of specific economy pairs and dimensions driving regional integration at bilateral as well as regional levels in Asia.

Recent trends indicate a decline in the RII of Asia since the onset of the pandemic in 2019, affecting all Asian subregions, except for a small uptick in 2021 for Southeast Asia. The decline was most rapid in Central Asia and South Asia. Despite this decline, Southeast Asia remains the most integrated with Asia, followed by the Pacific and Oceania, and East Asia. In 2000, Asia was most centered around Japan, with noticeable clusters for East Asia, South Asia, Southeast Asia, and the Pacific and Oceania. By 2021, subregional clusters are still observed, but the network is more centered around the PRC.

The conclusion of this study presents key proposals for subsequent research, aiming to improve the measure of regional integration. Firstly, expanding the estimation coverage by including more individual economies globally would broaden the scope of regional integration indexes. This involves computing regional integration indexes for regions beyond Asia and comparing them with the computed estimates for Asia's RII. This cross-regional comparison is essential for identifying benchmarks as well as unique patterns and variations in regional integration.

Secondly, the study suggests employing the same robust methodology used for regional integration to estimate global integration indexes. This allows for a comprehensive evaluation of the global economic landscape and facilitates a comparison with the regional integration index. Such a comparative analysis can provide insights into the relative significance of regional and global integration trends.

Thirdly, the model can be extended by introducing more state variables or additional dynamic factors for each dimension of RII, namely trade, FDI, finance, and migration, as shown by the sample estimation done for Thailand–Japan dimensional indexes. This enhancement aims to capture a more detailed representation of the complex and multifaceted nature of regional integration, refining the accuracy and depth of the analysis.

Lastly, further study could be undertaken to extend the analysis to explore the factors influencing the strength of integration between economy pairs and among economies within a specific region. Understanding these factors is crucial for policymakers and researchers, as it provides insights into the drivers and inhibitors of regional integration, enabling more informed decision-making.

These approaches and proposals will not only expand the geographic and analytic scope of the regional integration index studies but also deepen the understanding of the underlying factors shaping the strength and dynamics of economic integration at the bilateral, regional, and global levels.

## APPENDIXES

### Appendix A.1: Estimated Model Parameters

Let  $y_{it}^{(j)}$  be the  $j^{th}$  integration indicator  $j = 1, \dots, k$  for the  $i^{th}$  economy-pair  $i = 1, \dots, n$ , at time  $t = 1, \dots, T$ . The  $y_{it}^{(j)}$  can be expressed in a linear regression form and explained by a constant term  $C^{(j)}$ , the integration index  $BEI_{it}$  with its corresponding coefficient  $Z^{(j)}$ , and a random fluctuation  $\epsilon_{it}^{(j)}$ . Only  $y_{it}^{(j)}$  is observed, and the regressor  $BEI_{it}$  is assumed to be a latent variable. Given a pool of  $k$  integration indicators  $y_{it}^{(j)}$ ,  $BEI_{it}$  is estimated using the dynamic factor model, given by Rayp and Standaert (2017):

$$\begin{bmatrix} y_{it}^{(1)} \\ \vdots \\ y_{it}^{(k)} \end{bmatrix}' = \begin{bmatrix} C^{(1)} \\ \vdots \\ C^{(k)} \end{bmatrix}' + \begin{bmatrix} Z^{(1)} \\ \vdots \\ Z^{(k)} \end{bmatrix}' BEI_{it} + \begin{bmatrix} \epsilon_{it}^{(1)} \\ \vdots \\ \epsilon_{it}^{(k)} \end{bmatrix}' \quad (\text{A.1.1})$$

which, in matrix form yields:

$$\mathbf{y}_{it} = \mathbf{C} + \mathbf{Z} * BEI_{it} + \boldsymbol{\epsilon}_{it} \quad (\text{A.1.2})$$

where  $\mathbf{y}_{it}$ ,  $\mathbf{C}$ , and  $\mathbf{Z}$  are  $1 \times k$ . The error term is assumed to follow a normal distribution with a diagonal  $k \times k$  covariance matrix  $\mathbf{H}$ . The elements in  $\mathbf{Z}$  are called the factor loadings. The economy-couple equation can be stacked across  $i$ :

$$\begin{bmatrix} \mathbf{y}_{1t} \\ \vdots \\ \mathbf{y}_{nt} \end{bmatrix} = \mathbf{1}_n \otimes \mathbf{C} + \begin{bmatrix} BEI_{1t} \\ \vdots \\ BEI_{nt} \end{bmatrix} \otimes \mathbf{Z} + \begin{bmatrix} \boldsymbol{\epsilon}_{1t} \\ \vdots \\ \boldsymbol{\epsilon}_{nt} \end{bmatrix} \quad (\text{A.1.3})$$

$$\rightarrow \mathbf{Y}_t = \mathbf{1}_n \otimes \mathbf{C} + \mathbf{BEI}_t \otimes \mathbf{Z} + \boldsymbol{\epsilon}_t \quad (\text{A.1.4})$$

where  $\mathbf{Y}_t$  is  $n \times k$ ,  $\mathbf{BEI}_t$  is  $n \times 1$ , and  $\boldsymbol{\epsilon}_t \sim N(\mathbf{0}, \mathbf{I}_n \otimes \mathbf{H})$ . This equation can be viewed as the measurement equation of the state space model.  $\mathbf{BEI}_t$  is assumed to be an  $AR(1)$  process given by:

$$\mathbf{BEI}_t = \mathbf{T} * \mathbf{BEI}_{t-1} + \mathbf{v}_t \quad (\text{A.1.5})$$

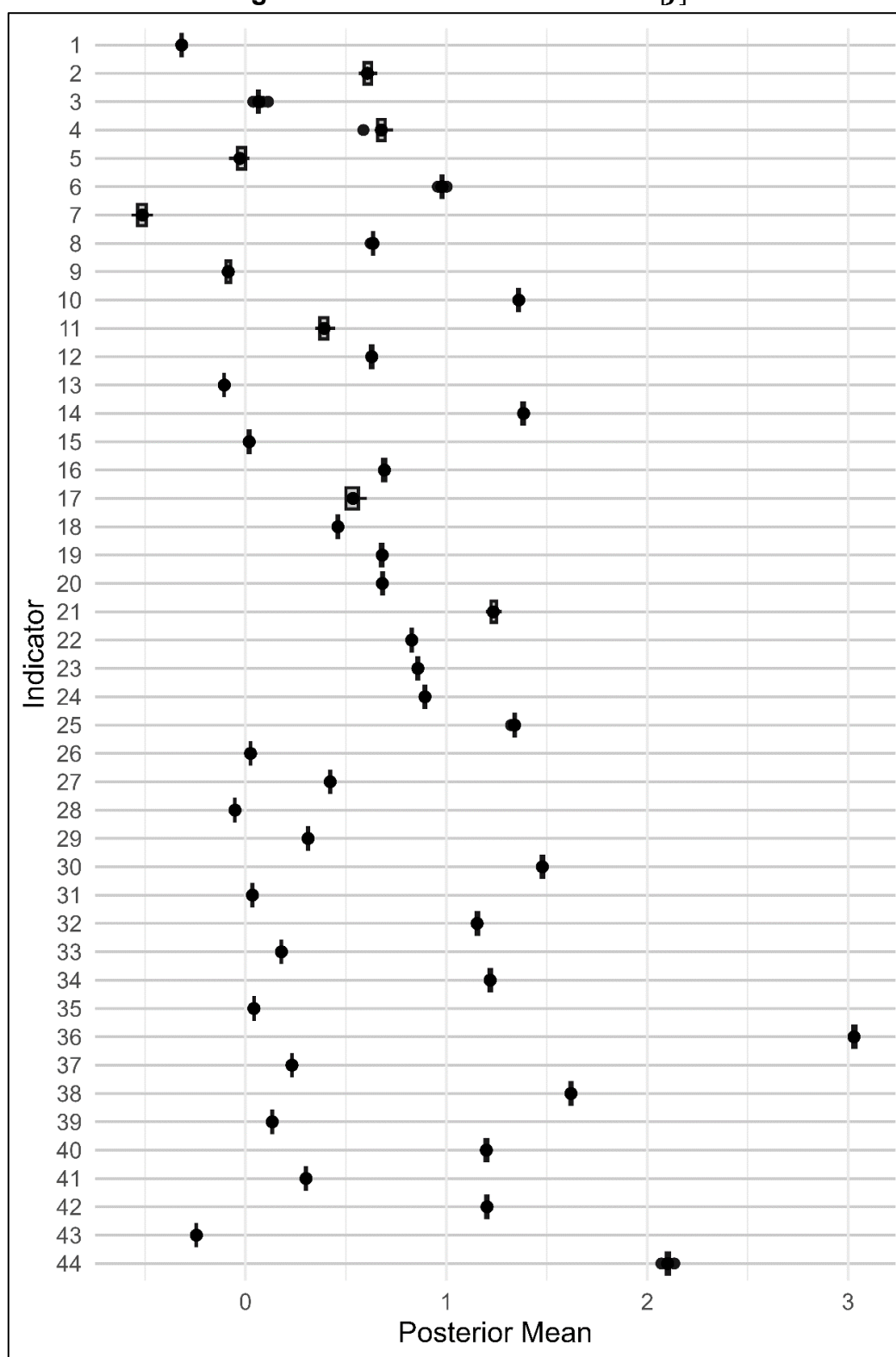


where  $\mathbf{T}$  is an  $n \times n$  diagonal matrix, and  $\mathbf{v}_t$  is normal with mean zero and an identity covariance matrix. The equation of  $\mathbf{BEI}_t$  is called the state equation of the state space model. Note that Rayp and Standaert (2017) assume that the parameters  $\mathbf{C}$ ,  $\mathbf{Z}$ , and  $\mathbf{H}$  are fixed across all economy-couples, and this restriction must be included in the estimation procedure.

The posterior means of the model parameters are calculated from the samples produced by Gibbs sampling. The 10 posterior means for the parameters of the measurement equation are presented in Figure A.1.1 for  $C$ , Figure A.1.2 for  $Z$ , and Figure A.1.3 for  $H$ . The black circle within the boxplot represents the average of the posterior means.

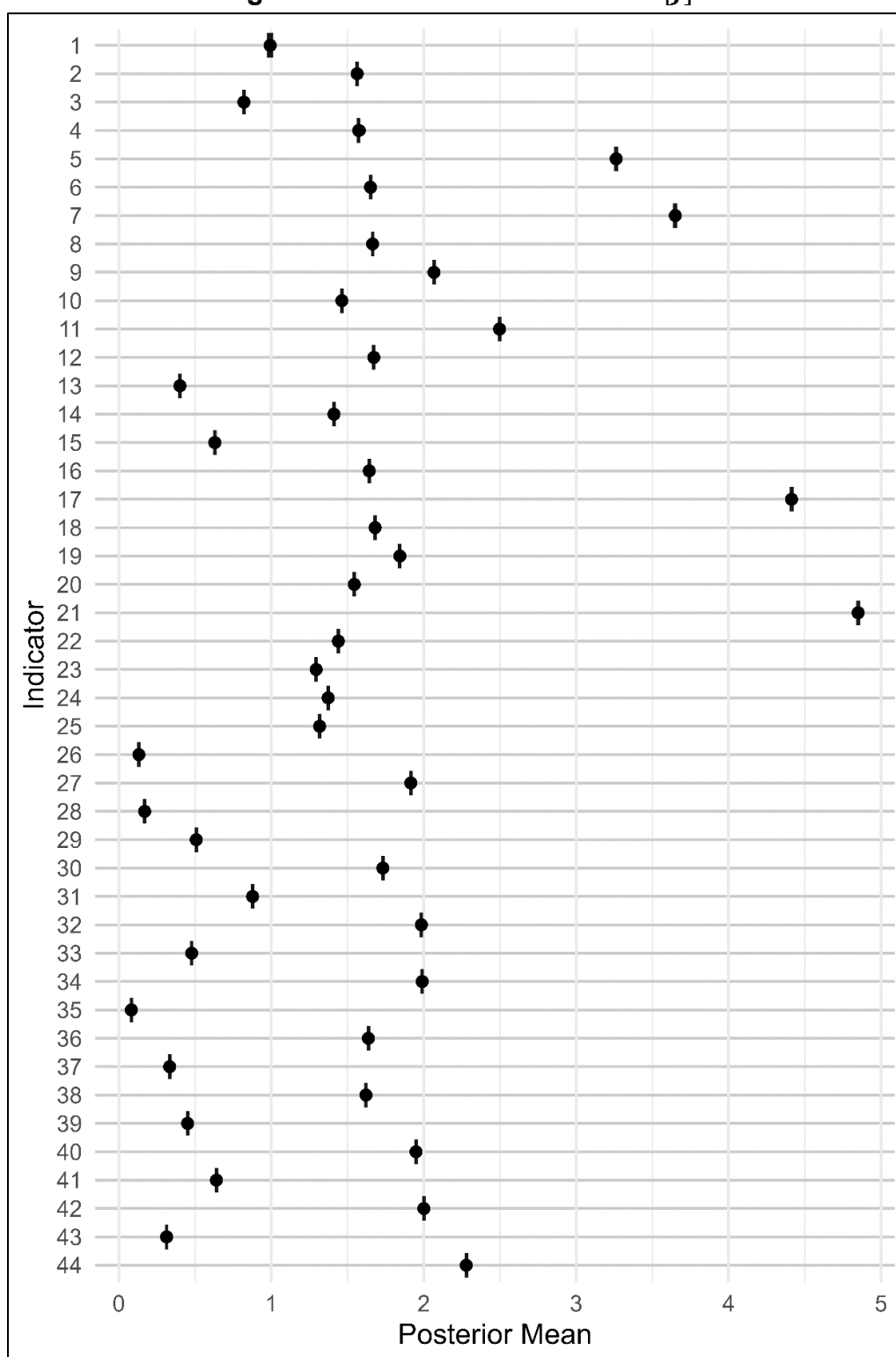
The vertical axis of the graphs represents the  $j^{th}$  integration indicator. The posterior means across the 10 chains have narrow ranges for the  $C$ ,  $Z$ , and  $H$  parameters, despite having different initial values. The small variability of posterior means across the 10 chains indicate convergence.

Figure A.1.4 shows the posterior means of the autoregressive parameter  $T$ , averaged across the 10 chains. The horizontal axis represents the  $i^{th}$  directional economy pair, while the vertical axis represents the magnitude of the first-order autoregression. Almost all directional economy pairs have a positive autoregressive estimated parameter, even as their initial values range from  $-1$  to  $1$ . This implies that a dynamic factor model adds benefit to extracting the integration indexes rather than treating the data as cross-sectional, as in the case in a simple average or principal components analysis.

Figure A.1.1: Posterior Mean of  $C[j]$ 

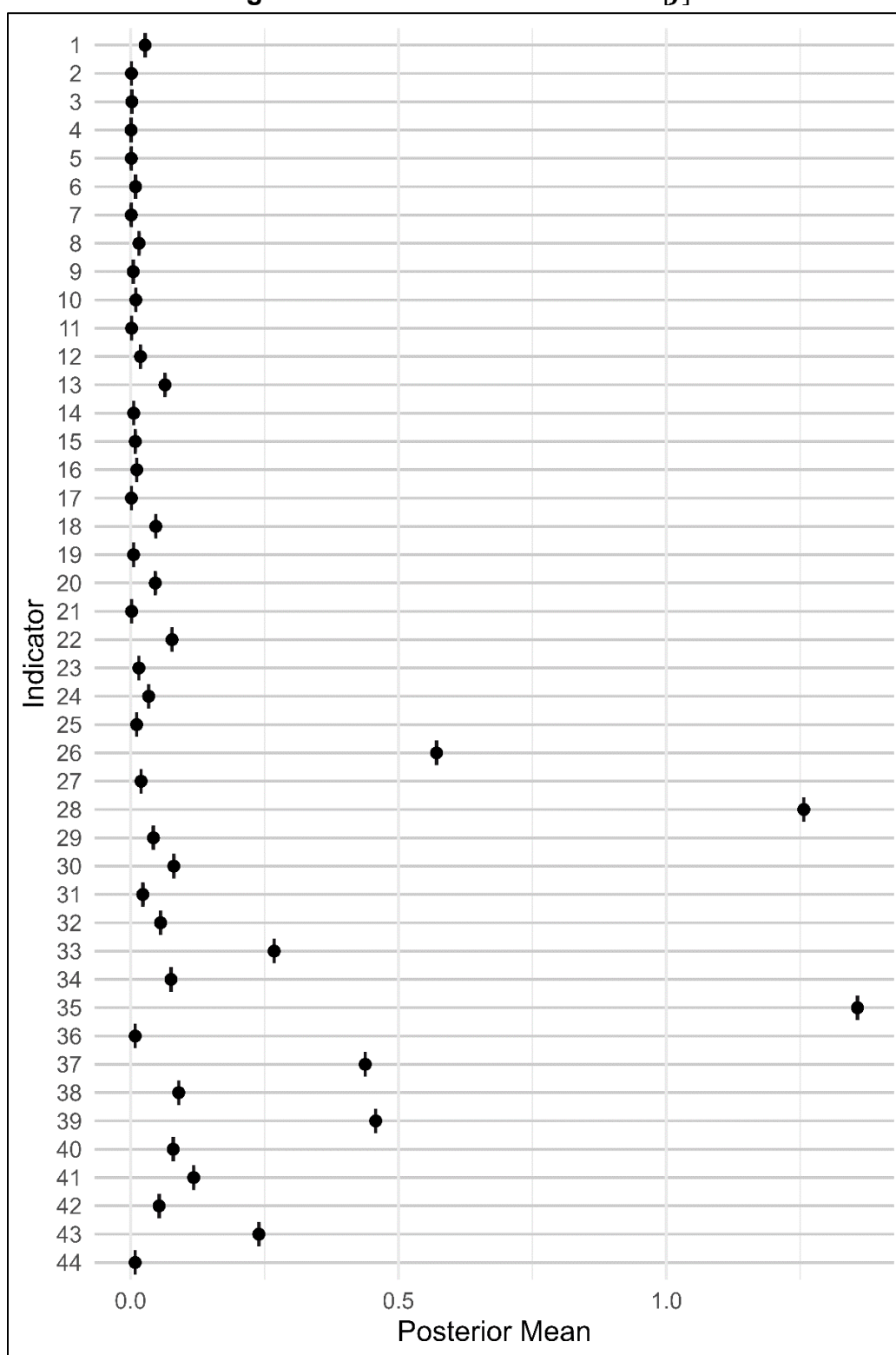
Note:  $C[j]$  is the intercept in the dynamic factor model.

Source: Authors' estimates.

Figure A.1.2: Posterior Mean of  $Z[j]$ 

Note:  $Z[j]$  is the bilateral economic integration (BEI) factor loading in the dynamic factor model.

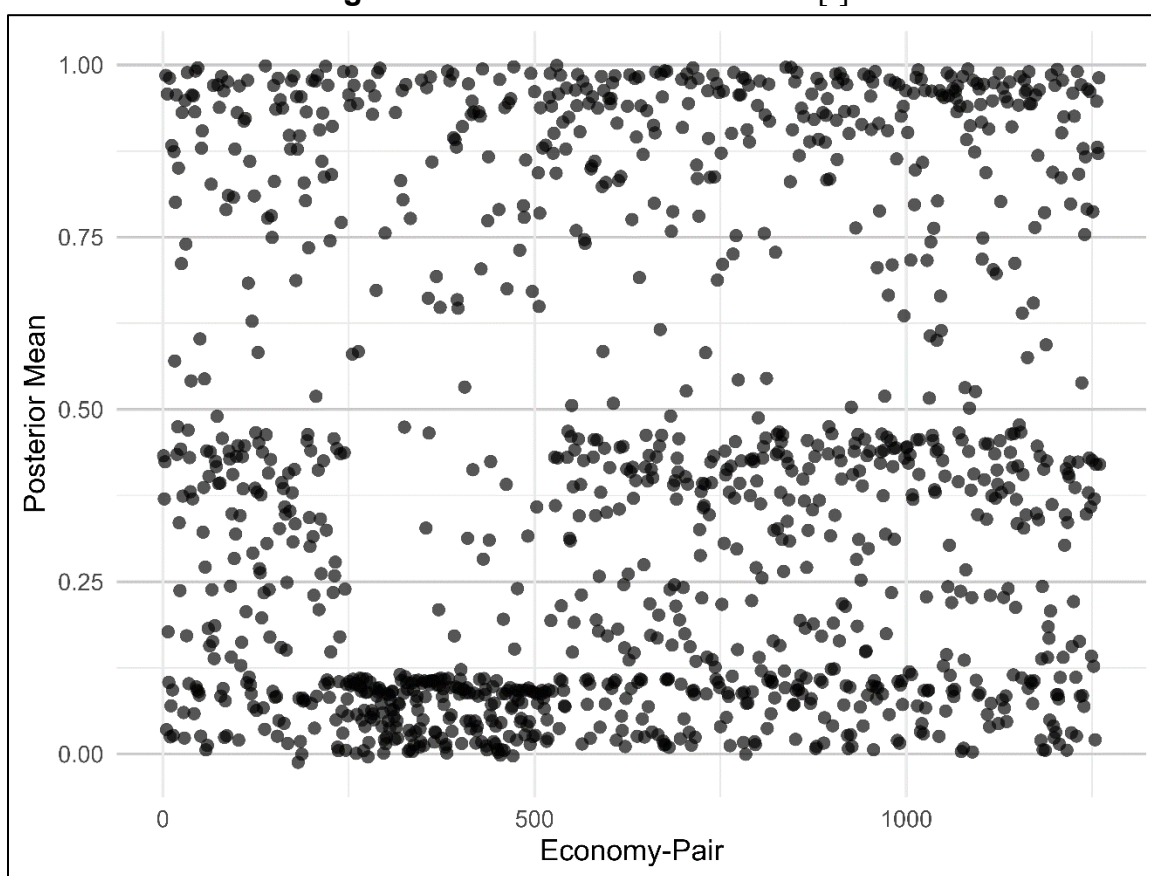
Source: Authors' estimates.

Figure A.1.3: Posterior Mean of  $H[j]$ 

Note:  $H[j]$  error variance of the dynamic factor model.

Source: Authors' estimates.

**Figure A.1.4: Posterior Mean of  $T[i]$**



Note:  $T[i]$  is the AR(1) parameter of the state equation,

Source: Authors' estimates.

## Appendix A.2: Regional Integration Indicators by Category

Category	Description	
Trade	1	Exports of manufactured goods, precious stones, nonferrous base metals, share of GDP <sup>c,d</sup>
	2	Exports of manufactured goods, precious stones, nonferrous base metals, share of total <sup>d</sup>
	3	Exports of primary commodities, except nonferrous metals, share of GDP <sup>c,d</sup>
	4	Exports of primary commodities, except nonferrous metals, share of total <sup>d</sup>
	5	Imports of manufactured goods, precious stones, nonferrous base metals, share of GDP <sup>c,d</sup>
	6	Imports of manufactured goods, precious stones, nonferrous base metals, share of total <sup>d</sup>
	7	Imports of primary commodities, except nonferrous metals, share of GDP <sup>c,d</sup>
	8	Imports of primary commodities, except nonferrous metals, share of total <sup>d</sup>
	9	Export: Transport, share of GDP <sup>c,f</sup>
	10	Export: Transport, share of total <sup>f</sup>
	11	Export: Travel, share of GDP <sup>c,f</sup>
	12	Export: Travel, share of total <sup>f</sup>
	13	Export: Other commercial services, share of GDP <sup>c,f</sup>
	14	Export: Other commercial services, share of total <sup>f</sup>
	15	Export: Goods-related services, share of GDP <sup>c,f</sup>
	16	Export: Goods-related services, share of total <sup>f</sup>
	17	Import: Transport, share of GDP <sup>c,f</sup>
	18	Import: Transport, share of total <sup>f</sup>
	19	Import: Travel, share of GDP <sup>c,f</sup>
	20	Import: Travel, share of total <sup>f</sup>
	21	Import: Other commercial services, share of GDP <sup>c,f</sup>
	22	Import: Other commercial services, share of total <sup>f</sup>
	23	Import: Goods-related services, share of GDP <sup>c,f</sup>
	24	Import: Goods-related services, share of total <sup>f</sup>
Foreign Direct Investment	25	BOP-based FDI inflows, share of GDP <sup>a,c</sup>
	26	BOP-based FDI inflows, share of total <sup>a</sup>
	27	BOP-based FDI outflows, share of GDP <sup>a,c</sup>
	28	BOP-based FDI outflows, share of total <sup>a</sup>
Finance	29	Equity inflows, share of GDP <sup>b,c</sup>
	30	Equity inflows, share of total <sup>b</sup>
	31	Equity outflows, share of GDP <sup>b,c</sup>
	32	Equity outflows, share of total <sup>b</sup>
	33	Long-term debt inflows, share of GDP <sup>b,c</sup>
	34	Long-term debt inflows, share of total <sup>b</sup>
	35	Long-term debt outflows, share of GDP <sup>b,c</sup>
	36	Long-term debt outflows, share of total <sup>b</sup>
	37	Short-term debt inflows, share of GDP <sup>b,c</sup>
	38	Short-term debt inflows, share of total <sup>b</sup>
	39	Short-term debt outflows, share of GDP <sup>b,c</sup>
	40	Short-term debt outflows, share of total <sup>b</sup>
Migration	41	Number of immigrants, share of total <sup>e</sup>
	42	Number of immigrants, share of population <sup>c,e</sup>
	43	Number of emigrants, share of total <sup>e</sup>
	44	Number of emigrants, share of population <sup>c,e</sup>

<sup>a</sup> Data from Bureau van Dijk. Zephyr M&A Database; and Financial Times. fDi Markets.

<sup>b</sup> Data from International Monetary Fund (IMF). Coordinated Portfolio Investment Survey (CPIS).

<sup>c</sup> Data from International Monetary Fund (IMF). World Economic Outlook; and World Bank. World Development Indicators database.

<sup>d</sup> Data from United Nations (UN) Commodity Trade (COMTRADE) Database.

<sup>e</sup> Data from United Nations (UN) International Migrant Stock.

<sup>f</sup> Data from World Trade Organization (WTO)–Organisation for Economic Co-operation and Development (OECD). Balanced Trade in Services (BaTIS) data set.

Source: Authors' compilation.

### Appendix A.3: List of Economies with Insufficient GDP Data

	<b>Economy Names</b>
1	Anguilla
2	Netherlands Antilles
3	Antarctica
4	French Southern Territories (the)
5	Bonaire, Sint Eustatius and Saba
6	Saint Barthélemy
7	Belgium-Luxembourg
8	Bouvet Island
9	Cocos (Keeling) Islands (the)
10	Cook Islands (the)
11	Curaçao and Sint Maarten
12	Christmas Island
13	Western Sahara
14	Falkland Islands (the) [Malvinas]
15	Guernsey
16	Gibraltar
17	Guadeloupe
18	French Guiana
19	Heard Island and McDonald Islands
20	British Indian Ocean Territory (the)
21	Jersey
22	Montserrat
23	Martinique
24	Mayotte
25	Norfolk Island
26	Niue
27	Pitcairn
28	Democratic People's Republic of Korea
29	French Polynesia
30	Réunion
31	Rwanda
32	Serbia and Montenegro
33	South Georgia and the South Sandwich Islands
34	Saint Helena, Ascension and Tristan da Cunha
35	Svalbard and Jan Mayen
36	Somalia
37	Saint Pierre and Miquelon
38	South Sudan
39	Sint Maarten (Dutch part)
40	Tokelau
41	United States Minor Outlying Islands (the)
42	Holy See (the)
43	Venezuela (Bolivarian Republic of)
44	Virgin Islands (British)
45	Wallis and Futuna
46	Kosovo
47	Yugoslavia

GDP = gross domestic product.

Source: Authors' compilation.

#### Appendix A.4: List of Economies with Insufficient Total Flows Data

<b>Data Issue</b>	<b>Economy</b>	
Insufficient total inflows	1	Andorra
	2	American Samoa
	3	Federated States of Micronesia
	4	Greenland
	5	Guam
	6	Marshall Islands
	7	Nauru
	8	Palau
	9	San Marino
Insufficient total outflows	10	Côte' d'Ivoire
	11	Curacao
	12	Cayman Islands
	13	Turks and Caicos Islands
Insufficient total inflows and total outflows	14	Isle of Man
	15	Liechtenstein
	16	Monaco
	17	Puerto Rico
	18	Virgin Islands
	19	Kosovo
	20	Bonaire, Sint Eustatius and Saba
	21	Channel Islands
	22	Western Sahara
	23	Cayman Islands
	24	Northern Mariana Islands
	25	Mayotte
	26	Rest of the World
	27	Saint Helena, Ascension and Tristan da Cunha
	28	Saint Pierre and Miquelon

Source: Authors' compilation.



**Appendix A.5: List of Economies in Asia by In-Degree  
(minimum of three connections)**

Year	Rank	Economy	Connections	RII
2000	1	JPN	11	0.407
	2	AUS	4	0.148
	3	PRC	4	0.148
	4	SIN	4	0.148
2001	1	JPN	12	0.444
	2	SIN	6	0.222
	3	PRC	5	0.185
	4	AUS	4	0.148
2002	1	JPN	11	0.407
	2	PRC	8	0.296
	3	SIN	6	0.222
	4	AUS	4	0.148
	5	IND	3	0.111
2003	1	JPN	12	0.444
	2	PRC	10	0.370
	3	SIN	5	0.185
	4	AUS	4	0.148
	5	IND	3	0.111
2004	1	PRC	11	0.407
	2	JPN	11	0.407
	3	SIN	5	0.185
	4	AUS	4	0.148
	5	IND	3	0.111
2005	1	PRC	11	0.407
	2	JPN	11	0.407
	3	SIN	5	0.185
	4	AUS	4	0.148
	5	IND	3	0.111
2006	1	PRC	11	0.407
	2	JPN	11	0.407
	3	SIN	5	0.185
	4	AUS	4	0.148
	5	IND	3	0.111
2007	1	PRC	13	0.481
	2	JPN	10	0.370
	3	SIN	5	0.185
	4	AUS	4	0.148
	5	IND	3	0.111
2008	1	PRC	13	0.481
	2	JPN	10	0.370
	3	SIN	5	0.185
	4	AUS	4	0.148
	5	IND	3	0.111
2009	1	PRC	12	0.444
	2	JPN	8	0.296
	3	AUS	4	0.148
	4	SIN	4	0.148
	5	IND	3	0.111
2010	1	PRC	15	0.556

*Continued of the next page*

Year	Rank	Economy	Connections	RII
	2	JPN	8	0.296
	3	SIN	6	0.222
	4	AUS	4	0.148
	5	IND	3	0.111
2011	1	PRC	16	0.593
	2	JPN	8	0.296
	3	AUS	4	0.148
	4	SIN	4	0.148
	5	IND	3	0.111
2012	1	PRC	18	0.667
	2	JPN	8	0.296
	3	SIN	5	0.185
	4	AUS	4	0.148
	5	IND	3	0.111
2013	1	PRC	19	0.704
	2	JPN	8	0.296
	3	SIN	5	0.185
	4	AUS	4	0.148
2014	1	PRC	20	0.741
	2	JPN	9	0.333
	3	AUS	4	0.148
	4	SIN	4	0.148
	5	IND	3	0.111
2015	1	PRC	21	0.778
	2	JPN	8	0.296
	3	SIN	5	0.185
	4	AUS	4	0.148
	5	IND	3	0.111
2016	1	PRC	21	0.778
	2	JPN	8	0.296
	3	SIN	5	0.185
	4	AUS	4	0.148
	5	IND	3	0.111
2017	1	PRC	22	0.815
	2	JPN	8	0.296
	3	SIN	5	0.185
	4	AUS	4	0.148
	5	IND	3	0.111
2018	1	PRC	22	0.815
	2	JPN	8	0.296
	3	SIN	5	0.185
	4	AUS	4	0.148
	5	IND	3	0.111
2019	1	PRC	22	0.815
	2	JPN	8	0.296
	3	SIN	5	0.185
	4	AUS	4	0.148
	5	IND	3	0.111
2020	1	PRC	23	0.852
	2	JPN	8	0.296
	3	SIN	5	0.185
	4	AUS	4	0.148

Year	Rank	Economy	Connections	RII
	5	IND	3	0.111
2021	1	PRC	24	0.889
	2	JPN	7	0.259
	3	AUS	4	0.148
	4	SIN	4	0.148
	5	IND	3	0.111

AUS = Australia, IND = India, JPN = Japan, PRC = People's Republic of China, RII = regional integration index, SIN = Singapore,

Source: Authors' estimates.

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## Estimating Regional Integration Using the Bayesian State-Space Approach

Estimating regional integration faces challenges due to incomplete data. This paper addresses this through the dynamic factor model estimated using the Bayesian state-space approach. Bilateral economic integration (BEI) indexes are estimated across four dimensions: trade, foreign direct investments, finance, and migration. The regional integration index (RII) of Asia and the Pacific is calculated by applying network density to the BEI estimates. The RII declined slightly in recent years, with the network centering more around the People's Republic of China.

### About the Asian Development Bank

ADB is committed to achieving a prosperous, inclusive, resilient, and sustainable Asia and the Pacific, while sustaining its efforts to eradicate extreme poverty. Established in 1966, it is owned by 68 members—49 from the region. Its main instruments for helping its developing member countries are policy dialogue, loans, equity investments, guarantees, grants, and technical assistance.

