

Technology diffusion, absorptive capacity, and income convergence for Asian developing countries: a dynamic spatial panel approach

Ji Uk Kim¹

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Abstract

In this paper, we analyze convergence in relative income using a technology diffusion model allowing for spatial interdependence among 11 Asian countries from 1970 to 2014. We compute impulse responses (absolute or conditional convergence) to stochastic productivity shock through sensitivity analysis using a two-country model. We then conduct spatial panel model estimation, decomposing marginal effects into direct (own country) and indirect (spillover) effects for a multicountry empirical model. Technology stock is measured according to the total factor productivity of the Asian country relative to that of the leader country, the USA. Through sensitivity analysis, we find that the results support both the absolute and conditional convergence hypotheses in the technology diffusion model. The dynamic spatial Durbin panel regression results with the Schumpeterian technological diffusion model and the extended neoclassical growth model support the conditional convergence hypothesis among Asian countries since the total effect on the lagged relative income is significant and negative. The total effects of human capital investment rate, total factor productivity, and trade on relative income growth are positive and significant, and most technology shock is transferred by absorption capacity in combination with trade in Asian countries.

Keywords Schumpeterian technological diffusion · Convergence · Absorptive capacity · Dynamic spatial Durbin panel model

JEL Classification $O4 \cdot O2$

[☑] Ji Uk Kim jiukim@cau.ac.kr

¹ Department of Economics, Chung-Ang University, 221 Heuksuk-dong, Dongjak-ku, Seoul 06974, Korea

1 Introduction

Many recent empirical studies have focused on international technology diffusion and income convergence. The degree of technology diffusion depends on the absorptive capacity of developing countries. Human capital, total factor productivity (TFP), and domestic R&D are related to the ability of developing countries to benefit from international technology transfer and contribute to their own technological progress. International trade and foreign direct investment (FDI) are considered to be two major channels for embodied knowledge spillover. Gaps in technology levels become smaller because technological advances in one economy are likely to be transmitted to other economies when technological spillovers are allowed. Furthermore, some empirical studies have used a spatial econometric framework to test country convergence. Assuming that a spatial lag or autoregressive term accounts for spatial dependence, the result is a faster convergence rate. If spatial dependence is present but omitted, this omission leads to unreliable statistical inference. Technological spillover and interdependence have direct (own country) and indirect (spillover) effects on the rate of convergence and are also embodied in unobserved individual effects.

A series of papers have considered spatial dependence on technology diffusion models. In particular, they document the significant role of geography in determining technology diffusion across countries. Easterly and Levine (1997) show that the growth effects of neighboring countries relate to location and focus on influences from physically adjacent locations to explain cross-country differences in public policies and other economic indications. Ades and Chua (1997) show that regional instability, defined as political instability in neighboring countries, has a strong negative effect on a country's economic performance. They argue that these adverse regional influences must be taken into account when projecting the future economic performance of countries. Comin et al. (2012) determine that understanding technology diffusion over space is crucial to understanding the speed of technology diffusion.¹ Spatial econometric methods allow for the estimation of interactions between countries and spatial dependence. Ertur and Koch (2007, 2011) estimate the rate of convergence in a spatial Solow model and a spatial Schumpeterian growth model. They use maximum likelihood methods for their estimations. Elhorst et al. (2010) estimate an extended Solow-Swan growth model using European regions. They estimate an unconstrained spatial Durbin model using general methods of moment (GMM), maximum likelihood, and a mixture of both, which allows the inclusion of fixed effects and spatial interaction effects. Fischer (2011) designs a reduced-form empirical spatial Mankiw, Romer, and Weil (MRW) model to assess the importance of cross-region technological interdependence for 198 regions across 22 European

¹ As a motivation, key papers exploring technology diffusion growth model without considering spatial interactions include Coe and Helpman (1995), Benhabib and Spiegel (1994, 2005), Sachs and Warner (1995), Caselli and Coleman (2001), Keller (2004), Engelbrecht (2002), Salinas-Jiménez (2003), Dowrick and Rogers (2002), Comin and Dmitriev (2013), Jones (2015), and Grossman and Helpman (2015). These authors, among others, explain how absorptive capacity facilitates technological catch-up.

countries from 1995 to 2004. Ho et al. (2013) show that there are positive spillover effects of growth from one country to its trade partners and that the implied rate of convergence is higher after including a spatial autoregressive term and a spatial time lag term. Lu and Wang (2015) adopt a spatial dynamic panel data approach and spatial quasi-maximum likelihood to reestimate the speed of growth convergence in 91 countries based on technological interdependence and spatial externalities. Lyncker and Thoennessen (2017) indicate that geographic clustering is quite pronounced in support of the club convergence in income of 194 European NUTS-2 regions.

Applications of the dynamic spatial panel data model from the very beginning are of Elhorst et al. (2010) on economic convergence (see Debarsy et al. 2012; Segura 2017; Ciccarellia and Elhorst 2017; Silva et al. 2017). Bouayad-Agha and Védrine (2010) found empirical evidence of conditional convergence of European 191 regions over the period 1980–2005, using a dynamic spatial panel data model. Technological diffusion due to spatial externalities plays a major role in the convergence pattern of European regions. Yu and Lee (2012) adopt a dynamic spatial panel approach to study regional growth convergence spanning the period 1930-2006 for the U.S. 48 contiguous states. They introduce technological spillovers into the neoclassical framework, showing that the convergence rate is higher and there is spatial interaction. Gallo and Fingleton (2014) present alternative approaches (distribution dynamics) to regional growth and convergence empirics for the EU, implying constant probabilities of different income states but allowing movement of regions across income states. Antai et al. (2015) focus on estimating a dynamic spatial panel data model with a specified source of endogeneity for the time-varying spatial weight matrices when the time period T is short. They propose the twostage instrumental variable (2SIV) estimation method and prove its consistency and asymptotic normality by employing the theory of asymptotic inference under near-epoch dependence. Lee and Yu (2016) apply the spatial Durbin dynamic panel models of under the two-stage least squares (2SLS) and maximum likelihood (ML) estimations to investigate the international spillover of economic growth through bilateral trade, showing that inclusion of Durbin terms can be important. Arbia and Paelinck (2003b) estimate regional convergence for 119 European regions using a Lotka–Volterra approach.² They estimate a difference equation system using ordinary least squares (OLS), where each region is represented by one equation, and use the stability conditions of this system to determine convergence. This approach implies that convergence depends on the parameters of the region itself as well as that of other regions. Following Arbia and Paelinck (2003a, b), Ditzen (2018) uses a general Lotka-Volterrra model to estimate convergence for 93 countries. This model employs an equation with a spatial time lag and common factors. The combination of spatial dependence and common factors has recently received attention in the literature and is summarized by Elhorst et al. (2016). The estimated model includes

 $^{^2}$ A Lotka–Volterra approach on a classical convergence equation without cross-sectional interactions confirms earlier empirical findings in the literature. However, strong cross-sectional dependence remains in these specifications, invalidating the results. In addition, this approach presents evidence for conditional convergence.

common factors and potentially heterogeneous slopes and dynamics in a way that is well motivated by the theoretical model and the current spatial econometrics literature (see Ertur and Musolesi 2017). Ditzen (2018) also considers multiple potential channels for cross-country spillovers captured by the spatial time lag. Here, the possible channels considered are trade, foreign direct investment, and high-skilled migration. After controlling for global spillovers using common factors, foreign direct investment and migration are found to produce the most substantial effects on spatial interactions. However, neither of these studies considered direct and indirect effects.

In this paper, we analyze convergence in relative income using a Schumpeterian technology diffusion model, allowing for spatial interdependence among 11 Asian countries from 1970 to 2014. Following the technological progress (horizontal innovation) described in the product variety model (Barro and Sala-i-Martin 1997, 2004; Novales et al. 2009) in Sect. 2, we demonstrate the technology transfer mechanism from a leading country in innovation to a follower country in imitation. Through sensitivity analysis, we demonstrate that our results support both the absolute and conditional convergence hypotheses even in the Schumpeterian technology diffusion model. We allow knowledge spillover and spatial interdependence among Asian countries in Sect. 3. Technology stock is measured as the total factor productivity (TFP) of the Asian country relative to that of the leader country, which in our models is the USA. This is regarded as a technology transfer mechanism. The product of the two variable ratios can represent the absorption capacity for accepting the technology of a leader country. Asian countries have a considerable geographical distance from the USA. The USA, the technological leader, is not included in the spatial weights and as a cross-sectional unit in this paper.³ The diffusion of technological innovation from the USA spreads through transactions such as FDI (field investment type), productivity, or trade between Asian countries and the USA, and the analysis of existing technology diffusion models that do not consider spatial interdependency. However, we consider general interaction patterns with the complete structure of interaction between Asian countries. According to the distance weight, technology diffusion is only considered among Asian countries. We derive the empirical equations, CAP model, and GAP model from the Schumpeterian technology diffusion model (vertical innovation) in line with Ertur and Koch (2011), and the NEO model from the neoclassical technology diffusion model in line with Ertur and Koch (2007) and Fischer (2011, 2018).

³ Ertur and Koch (2011) model the USA as the technological leader, but the USA remains a cross-sectional unit in their analysis and is therefore represented as a row in the variables, and a row and column in the spatial weight matrix. The sample contains 7 African countries, 21 North and South American countries, 9 Asian countries, 20 European countries, and 2 Oceanic countries. However, we only consider data for the 11 Asian countries.

If we follow the line with Ertur and Koch (2011), we have to model Japan as the technological leader in Asian region.⁴ We assume that not only does the technology leader spread knowledge to Asian countries, but also that Asian countries contribute to technology diffusion to the leading country. We consider general interaction patterns with the complete structure of interaction between Asian countries. We then test the extended Ertur and Koch growth model (*EK*12_*NEO model* and *EK*12_*CAP model*) allowing spatial interdependence among 12 Asian countries to test the convergence hypothesis in Sect. 4.4. We also analyze whether the rate of income convergence between Asian countries including Japan is slowing or accelerating. This is because Japan (advanced country) and Asian developing countries may have different steady states of income. The convergence rate may be slower than when Japan is not included.

Following Lesage and Pace (2009) and Elhorst (2012, 2014), we estimate an unconstrained dynamic spatial Durbin panel model (DSDM) using a maximum likelihood, which allows for the inclusion of fixed effects and spatial interaction effects. Following LeSage and Pace (2009), we also estimate the direct, indirect, and total effects to yield an interpretation of the spatial spillover effects. This rest of the paper is organized as follows. Section 2 presents a model of Schumpeterian technological diffusion between two countries and shows the absolute and conditional convergence through the impulse responses to stochastic productivity shock. Section 3 establishes the dynamic spatial Durbin panel model that considers spatial interdependence. Section 4 is devoted to our empirical findings and results of estimation for the dynamic spatial panel model. Section 5 concludes the paper.

2 The Schumpeterian technological diffusion and convergence

2.1 The technological diffusion model

We consider the Schumpeterian growth model elaborated by Aghion and Howitt (1992), Howitt (2000), and Ertur and Koch (2011). We also follow the technological diffusion model described by Barro and Sala-i-Martin (1997, 2004) and Novales et al. (2009). Technological innovation can lead to an increase in the variety of producer products (horizontal innovation). Copying or adapting an intermediate good from the leader country to be used in a follower country has a fixed cost. However, the cost of adapting commodities from the leader country is usually lower than the cost of innovation. The follower country benefits from the low costs of imitation and advantages with respect to the discovery or implementation of frontier technologies. There is room for exploration of mechanisms of technology diffusion, including the interaction between innovation and technology diffusion. The final good is produced

⁴ This is because Ertur and Koch (2011) indicate in the paper that, "the elasticities from Japan to South East Asian countries are also higher than the elasticities from Japan to other countries. These results suggest that the United States is a natural technological leader for Central and Southern American countries and that Japan is the technological leader in South East Asia." (p. 248).

in a country according to the production function, and the law of motion of stochastic productivity is:

$$Y_{t} = A_{t}L_{t}^{1-\alpha} \int_{0}^{Q_{t}} x(v)_{t}^{\alpha} dv = \theta_{t}AL_{t}^{1-\alpha} \int_{0}^{Q_{t}} x(v)_{t}^{\alpha} dv, \quad 0 < \alpha < 1,$$

$$\ln \theta_{t} = \phi \ln \theta_{t-1} + \varepsilon_{t}, \varepsilon_{t} \sim \text{ iid } N(0, \sigma_{\varepsilon}^{2}), \quad 0 < \phi < 1,$$
(1)

where Y_t and L_t denote the output of the final good and the labor input at time t, Q_t measures the number of product varieties, and $x(v)_t$ is the flow output of the v-th intermediate good $v \in [0, Q_t]$ used at time t. We assume for simplicity a constant labor supply, $L_t = L, \forall t$. The level of technology $A_t = \theta_t A$ is random, and $\ln \theta_t$ evolves according to an autoregressive process with random innovation, ε_t . Based on the profit maximization condition for the producer of the final good, we find that monopoly prices for intermediate goods are all the same, $P_{vt} = P = 1/\alpha$. With these monopoly prices, the demand for each intermediate good is $x_{vt} = x_t = L(\theta_t A \alpha^2)^{1/(1-\alpha)}$. A representative household maximizes the expected value of discounted time aggregate utility over an infinite horizon, with the single period budget constraint represented as

$$\max_{\{c_t, a_{t+1}\}} U = E_0 \sum_{t=0}^{\infty} \beta^t \frac{c_t^{1-\sigma} - 1}{1 - \sigma}, \text{ st. } c_t + a_{t+1} = w_t + (1 + r_t)a_t.$$
(2)

where β is the discount rate, c_t is consumption per capita, σ is a constant relative risk aversion, a_t is per capita assets, w_t is the wage rate, and r_t denotes the interest rate. The representative consumer solves the optimization problem subject to budget constraints. The leader country is labeled as country 1 and the follower country as country 2.

The follower country can either copy goods that were previously invented in the leader country or innovate and develop its own intermediate goods. We also assume that shocks in the leader country influence the follower country, while shocks in the follower country do not affect the leader country. Adapting an intermediate good to be used in country 2 requires a fixed cost, v_{2t} . v_{2t} increases with the proportion of commodities that has been copied by country 2 such as, $v_{2t} = \eta_2 \left(\frac{Q_{2t-1}}{Q_{1t-1}}\right)^b$ where η_2 is the fixed cost of imposition $Q_{2t} = Q_{2t}$ the fixed cost of innovation, $Q_{2t} < Q_{1t}$, and b > 0 is the elasticity of imitation cost function. When $Q_{2t-1} < Q_{1t-1}$, the cost of imitation will be lower than the cost of innovation, $v_{2t} < \eta_2$. The country 2 starts with fewer intermediate goods than the country 1: $Q_{20} < Q_{10}$ and $v_{20} < \eta_2$. We assume that an agent who pays v_{2t} would obtain a perpetual production monopoly for that intermediate good of country 2. The present value from imitating the *v*-th intermediate good in country 2 is the same as the imitation cost if there is free entry. Expressions in country 2 for the quantities of the intermediate good produced and of total output, as well as the flow of monopoly profits, are similar to those equations in country 1. By the same argument, the representative consumer solves the optimization problem subject to budget con- $\mu_{1t} \equiv \theta_{1t}^{\frac{1}{1-\alpha}}, \quad A_1' \equiv \frac{A_1^{\frac{1}{1-\alpha}} \alpha^{\frac{\alpha}{1-\alpha}} (1-\alpha)}{n_t / L_1},$ auxiliary variables, introduce straints. We

 $q_{1t} \equiv \frac{\eta_1}{L_1}Q_{1t}$, and $z_{1t} \equiv \frac{c_{1t}}{q_{1t}}$ for country 1 and then characterize the transitional dynamics of the economy and introduce auxiliary variables, $\mu_{2t} \equiv \theta_{2t}^{\frac{1}{1-\alpha}}, A'_2 = (1-\alpha^2)A_2^{\frac{1}{1-\alpha}}\alpha^{\frac{2\alpha}{1-\alpha}}L_2, q_{2t} \equiv \frac{\eta_2}{L_2}Q_{2t}, z_{2t} \equiv \frac{c_{2t}}{q_{2t}\alpha}$ for country 2. Therefore, we can express the relationship $q_{1t+1}/q_{1t} = \mu_{1t}A'_1(1+\alpha)\alpha^{\frac{1}{1-\alpha}} + 1 - z_{1t}$ for country 1. By combining the global constraint of resources and the Euler condition and describing the imitation cost function written in terms of these new variables, we have a system of two dynamic equations: a control variable, z_2 ; and a state variable, v_2 . It is important to note that $\{\mu_{1t}\}$ and $\{z_{1t}\}$ are obtained for the country 1, but affect the country 2. Hence, shocks in country 1 influence country 2, while shocks in country 2 do not affect country 1. We introduce variables in log differences with respect to the steady state: $\hat{z}_{2t} = \ln\left(\frac{z_{2t}}{z}\right)$ and $\hat{\mu}_{2t} = \ln(\mu_{2t})$. Hence, the approximation of two dynamic equations can be written as,

$$\Gamma_{0}\left(\begin{array}{c}E_{t}\hat{z}_{2t+1}\\\hat{v}_{2t+2}\end{array}\right) + \Gamma_{1}\left(\begin{array}{c}\hat{z}_{2t}\\\hat{v}_{2t+1}\end{array}\right) + \Gamma_{2}\left(\begin{array}{c}\hat{\mu}_{2t}\\\hat{z}_{1t}\\\hat{\mu}_{1t}\end{array}\right) = 0, \Rightarrow \left(\begin{array}{c}E_{t}\hat{z}_{2t+1}\\\hat{v}_{2t+2}\end{array}\right) = \Gamma_{3}\left(\begin{array}{c}\hat{z}_{2t}\\\hat{v}_{2t+1}\end{array}\right) + \Gamma_{4}\left(\begin{array}{c}\hat{\mu}_{2t}\\\hat{z}_{1t}\\\hat{\mu}_{1t}\end{array}\right),$$
(3)

where $\Gamma_3 = -\Gamma_0^{-1}\Gamma_1$, $\Gamma_4 = -\Gamma_0^{-1}\Gamma_2$. A well-determined equilibrium arises when Γ_3 has one stable and one unstable eigenvalue.⁵ { μ_{1t} } and { z_{1t} } are obtained for the country 1 that affects the country 2. The shocks { θ_{1t} } and { Q_{1t} } in the country 1 influence the country 2. By computing the numerical solution to the model, we obtain the relationships { y_{1t} } = and { y_{2t} }. The steady state level of output for the leading and following country is obtained by

$$Y_{1t} = L_1 A_1^{\frac{1}{1-\alpha}} \alpha^{\frac{2\alpha}{1-\alpha}} \theta_{1t}^{\frac{1}{1-\alpha}} Q_{1t} \text{ and } Y_{2t} = L_2 A_2^{\frac{1}{1-\alpha}} \alpha^{\frac{2\alpha}{1-\alpha}} \theta_{2t}^{\frac{1}{1-\alpha}} Q_{2t}$$
(4)

2.2 Absolute and conditional convergence

Through sensitivity analysis, we determine whether this result supports the absolute or conditional convergence hypothesis, which follow the neoclassical growth model. We start from realizations for stochastic productivity shock in country 1 rather than for productivity shocks in both countries. We assume that the time series for the productivity shock in country 2 is set to zero at all points in time. While computing the numerical solution to the model (3), we used the benchmark parameterizations physical capital share of final good sector $\alpha = 0.36$, discount factor $\beta = 0.96$, impulse shock of size in the leading country $\varepsilon_1 = 0.1$, and inverse of the intertemporal elasticity of substitution $\sigma = 1.5$ as common parameters in the literature, Novales et al. (2009) and Benhabib et al. (2017). The calibrated parameters are technology level of final good sector $A_1 = 1$, population size $L_1 = 1$, innovation cost $\eta_1 = 1$, persistence parameter of the stochastic process of shock in sector of final good $\phi_1 = 0.9$, standard deviation of the innovation in the stochastic process for theta $\sigma_{\varepsilon_1} = 0.0$ for the

⁵ If we eliminate unstable paths, the solution to the dynamic system will be stable, having a saddle path.

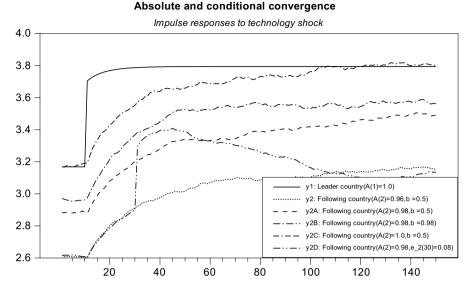


Fig. 1 Absolute and conditional convergence: Impulse responses of income per capita to technology shock. (1) All variables are detrended. (2) y1: income per capita for leader country, y2–y2D: income per capita for following country. (3) The vertical axis represents the per capita income, and the horizontal axis represents the flow of time

leader country. Impulse responses to a productivity shock in country 1 at time 10 of ε_1 =0.1 are computed. Figure 1 shows that all detrended per capita income variables experience permanent effects due to shocks in productivity. We obtain income (y1) in country 1, where it increases and shows the fastest adjustment to new steady state levels.

Figure 1 also shows the time evolution of incomes in country 2 for sensitivity analysis at different values of parameters in Table 1. The calibrated parameters for follower country are $A_2 = 0.96$ ($< A_1 = 1$), $L_2 = 1$, $\eta_2 = 1$, $\phi_2 = 0.9$, $\sigma_{\epsilon^2} = 0.001$, and elasticity of the imitation cost function b=0.5. However, income (y2) in country 2 increases more gradually and approaches new higher steady state levels. We generate the income realization y2A for the technology level of the final good sector with $A_2 = 0.98$ and elasticity of the imitation cost function with b = 0.5. y2A approaches a new higher steady state level than y2 with $A_2 = 0.96$ and b = 0.5. We assume that elasticity of the imitation cost function increases with b=0.98, maintaining $A_2 = 0.98$. The time series for consumption y2B shows higher transitional dynamics than that of y2A but eventually approaches the same steady state level as y2A. These results in the Schumpeterian technology diffusion model support the conditional convergence hypothesis. In a steady state, this benchmark model tends to generate a pattern of convergence for growth rate. Simulation y2C uses $A_2 = 1$ and b=0.5, where the technology level of the final good sector is greater than $A_2=0.98$. The income (y2C) realization converges to the level of y1 in country 1. This result in the Schumpeterian technology diffusion model supports the absolute convergence hypothesis. We then consider stochastic productivity shocks in both countries. After

Parameters: basic values	Sensit	Sensitivity analysis				
	y1	y1 y2	y2A	y2B	y2C	y2D
$ \begin{aligned} & \alpha = 0.36, \beta = 0.96, \sigma = 1.5, L_1 = 1.0, \eta_1 = 1.0, \\ & \phi_1 = 0.9, \varepsilon_1 = 0.1, \sigma_{\epsilon 1} = 0.0, L_2 = 1.0, \eta_2 = 1.0, \\ & \phi_2 = 0.9, \varepsilon_2 = 0.00, \sigma_{\epsilon 2} = 0.001 \end{aligned} $	$A_1 =$	1.0 $A_2 = 0.96, b =$	$0.5 A_2 = 0.98, b =$	$=0.5 A_2 = 0.98, b = 0.98$	$A_2 = 1.0, b = 0.5$	$A_1 = 1.0$ $A_2 = 0.96$, $b = 0.5$ $A_2 = 0.98$, $b = 0.5$ $A_2 = 0.98$, $b = 0.98$ $A_2 = 1.0$, $b = 0.5$ $A_2 = 0.98$, $b = 0.5$, $\varepsilon_{21}(30) = 0.08$
α : Physical capital share of final good sector, β : discount factor, ε_1 : impulse shock of size in the leading country, σ : inverse of the intertemporal elasticity of substitution, $A = A + i$ schedow laval of final good sector in leading country and following country measured.	discount f	actor, ε_1 : impulse	shock of size in the	e leading country, σ : ir	Iverse of the intert	emporal elasticity of substitution,

 Table 1
 Absolute and conditional convergence: sensitivity analysis

 A_1, A_2 : technology level of final good sector in leading country and following country, respectively, L_1 : population size η_1 : innovation cost, ϕ : persistence parameter of the stochastic process of shock in sector of final good, σ_{e_1} : standard deviation of the innovation in the stochastic process, and b : the elasticity of imitation cost function. $\varepsilon_{21}(30)$: a shock in country 2 at time 30 an impulse shock in country 1 at time 10 of $\varepsilon_1 = 0.1$, shocks in country 2 at time 30 of $\varepsilon_{21} = 0.08 (\langle \varepsilon_1 = 0.1 \rangle)$, follow sequentially.⁶ We compute two income variables, y2D from a shock of $\varepsilon_{21}(30)$. However, these values eventually approach new lower steady state levels than in country 1. This result supports the conditional convergence hypothesis, which follows the neoclassical growth model.

Conclusively, these results support both the absolute and conditional convergence hypotheses, which follow the neoclassical growth model. Improvements in government policy and technology level represented by increases in A_2 cause country 2 to become intrinsically superior. This indicates that the government of country 2 should adopt policies that are more favorable to incentives encouraging production and investment or more effective enforcement of property rights. Numerical analysis suggests that, when the government is more efficient, imitation cost becomes more elastic, technological shock is greater, and technological absorptive power is greater, convergence to the leading country becomes faster.

3 The dynamic spatial Durbin panel model

Ertur and Koch (2011) consider a multicountry Schumpeterian growth model introducing technological diffusion. They assume that this productivity parameter is defined as follows: $\lambda_i = \lambda \prod_{j=1}^n {\binom{A_{ji}}{A_{ii}}}^{r_i v_{ij}}$ where the v_{ij} parameters present the specific access of country *i* to the accumulated knowledge of all countries, and productivity is a function of technology gap ${\binom{A_{ji}}{A_{ii}}}$ of country *i* with respect to its own technology frontier. The v_{ij} parameters present the specific access of country *i* to the accumulated knowledge of all other countries, assuming $\sum_{j=1}^n v_{ij} = 1$ for i = 1, ..., n. This hypothesis can be as international spillover effect or as spatial externalities. The parameter $\gamma_i > 1$ measures the absorption capacity of country *i* which is assumed to be a function of aggregate physical capital accumulation and steady state analysis, they obtain the following econometric reduced form:

$$\ln y_{it} = \beta_0 + \beta_1 \ln \frac{s_{K,i}}{n_i + 0.05} + \theta H_i \sum_{j \neq i}^n v_{ij} \ln \frac{s_{K,j}}{n_j + 0.05} + \gamma H_i \sum_{j \neq i}^n v_{ij} \ln y_j + \varepsilon_i,$$
(5)

where s_K is the investment rate, n_i is the population growth rate, the coefficient θ is associated with the investment rate in physical capital divided by the effective depreciation rate of foreign country j, for j = 1, ..., n, and $\gamma > 0$ is the spatial autocorrelation coefficient. They should therefore be estimated using the appropriate spatial econometric methods.

$$y_t = \delta W y_t + X_t \beta + W X_t \theta + \mu + \xi_t I_N + \varepsilon_t$$
(6)

⁶ It is reasonable that the size of shocks in the follower country is smaller than that in the leader country.

where y_t denotes an $N \times 1$ column vector of the dependent variable for every unit (i = 1, ..., N) in the sample at time t (t = 1, ..., T), which represents the relative income between follower and leader countries. X_t presents an $N \times K$ matrix of explanatory variables. All variables are measured in logarithms. The $N \times N$ matrix W is a nonnegative weight matrix constructed from geographical distance. Since the spatial econometric model in Eq. (6) contains both X and WX variables, it is known as a spatial Durbin model. The vectors $\mu = (\mu_1, \mu_2, ..., \mu_N)'$ represent spatial fixed effects, and $\xi_t I_N$ represent time-period fixed effects where I_N is an $N \times 1$ column vector of ones. The $N \times 1$ vector $\varepsilon_t = (\varepsilon_{1t}, ..., \varepsilon_{Nt})'$ consists of *i.i.d.* disturbance terms, which have zero mean and finite variance σ^2 .

3.1 DSDM for Schumpeterian technology diffusion model (CAP model)

We develop a specification that explicitly includes this technological interdependence. The model will be estimated with a spatial econometric specification. The result obtained from the previous Sect. 2 supports the convergence hypothesis in the Schumpeterian technology diffusion model. Using the diffusion model results, the growth rate of production per worker in country 2 can be expressed in the following form:

$$\gamma_2 = \frac{\frac{dy_2}{dt}}{y_2} = \frac{\dot{y}_2}{y_2} = \gamma_1 + G\left[\frac{y_2}{y_1}, \left(\frac{y_2}{y_1}\right)^*\right],\tag{7}$$

where $\gamma_2 = \frac{\dot{y}_2}{y_2}$ is the growth rate of per worker income in follower country, $\left(\frac{y_2}{y_1}\right)^*$ is the steady state income level, and γ_1 is the growth rate of leading economy. The partial derivatives of the function *G* satisfy $G_1 < 0$, $G_2 > 0$, and $G(\cdot, \cdot) = 0$ if $\frac{y_2}{y_1} = \left(\frac{y_2}{y_1}\right)^*$. Country 2's growth rate $\frac{\dot{y}_2}{y_2}$ exceeds γ_1 if $\frac{y_2}{y_1} < \left(\frac{y_2}{y_1}\right)^*$. If the government of country 2 adopts policies that are more favorable to production and investment, the change in policy amounts to an increase in A_2 . In this case, $\left(\frac{y_2}{y_1}\right)^*$ increases, and the growth rate $\frac{\dot{y}_2}{y_2}$ increases on impact. This means that the result exhibits conditional convergence.⁷ We now generalize the two-country model to a multicountry model where all countries follow the leader country. As in Eq. (7), the growth rate of country *i* can be written as:

$$\log\left(\frac{y_{it}}{y_{it-1}}\right) = \log\left(\frac{y_{1t}}{y_{1t-1}}\right) - \omega\left[\log\left(\frac{y_{it}}{y_{1t}}\right) - \log\left(\frac{y_i}{y_1}\right)^*\right] = \varphi + \log\left(\frac{y_{1t}}{y_{1t-1}}\right) - \omega\left[\log\left(\frac{y_{it}}{y_{1t}}\right)\right],$$
(8)

where y_{it} and y_{1t} are the per capita income of the following country *i* and leader country 1 at time t, respectively, $\varphi = \omega \left[\log \left(\frac{y_i}{y_1} \right)^* \right]$, and ω is the speed of conver-

⁷ The growth rate of the follower \dot{y}_2/y_2 declines as y_2/y_1 rises for a given value of $(y_2/y_1)^*$. Also, for given y_2/y_1 , \dot{y}_2/y_2 rises with $(y_2/y_1)^*$. In other words, the growth rate of the follower is an increasing function of distance to its steady state.

gence necessary to reach the income level of the leader country in the diffusion model. Similar to the procedure of beta convergence based on the neoclassical growth model, Eq. (8) can be written as

$$\log\left(\frac{y_{it}}{y_{1t}}\right) = \epsilon + b\log\left(\frac{y_{it-1}}{y_{1t-1}}\right) = \epsilon + b\left(\frac{1}{1-\alpha}\right)\log\left[\left(\frac{A_i}{A_1}\right)\left(\frac{\theta_{it-1}}{\theta_{1t-1}}\right)\right] + b\log\left(\frac{Q_{it-1}}{Q_{1t-1}}\right),\tag{9}$$

where $\log\left(\frac{y_{it}}{y_{1t}}\right)$ represents the relative income between follower and leader countries, $\epsilon = \frac{\varphi}{1+\omega}$, and $b = \frac{1}{1+\omega}$. Let $R_{it} = q_{it} - q_{it-1}$, where $q_{it} = \log\left(\frac{y_{it}}{y_{1t}}\right)$. The ratio of output per worker in both countries depends on the ratios $\frac{\theta_{it}}{\theta_{1t}}$ and $\frac{Q_{it}}{Q_{1t}}$, where direct measures of Q_1 and Q_i or θ_1 and θ_i would not generally be available. The ratio of intermediate good number $\frac{Q_{it}}{Q_{1t}}$ or the ratio of technology shock $\frac{\theta_{it}}{\theta_{1t}}$ is replaced by $ga_{it} = \frac{tfp_{it}}{tfp_{1t}}$, where tfp_{it} and tfp_{1t} are TFP of the follower country and leader country, respectively. The ratio of TFP (gap) is considered to be a technical shock coming from leader country. This is regarded as a technology transfer mechanism. Furthermore, the product of the two variable ratios can represent absorption capacity to accept the technology of a leader country.

We assume that the ratio of TFP (gap) is influenced by physical capital externalities because of learning by doing. In line with Ertur and Koch (2011), we assume the following form for the level of technology in region *i* at time *t*, $g_{it} = \frac{\dot{A}_{it}}{A_{it}} = \lambda \sigma k_{it}^{\varphi} \prod_{j=1}^{n} \left(\frac{A_{jt}}{A_{it}}\right)^{\gamma_i v_{ij}}$ where λ represents productivity parameter, A_{jt} aggregate level of technology for region *j*, and k_{it} per worker physical capital.⁸ The technical parameter φ with $0 \le \varphi < 1$ represents the magnitude of externalities generated by k_{it} within region *i*, respectively. Each region has differentiated access to foreign technology because of the connectivity terms, denoted by W_{ij} . We assume that *W* is a weight matrix based on coordinates. The absorption capacity of country *i* (abs_i) is also assumed to be a function of human capital or foreign direct investment as $\gamma_i = \gamma abs_i$. The empirical equation for the growth rate of relative income of the technology diffusion model can be written as,⁹

$$R_{it} = \beta_0 + \beta_1 q_{it-1} + X_t \mathbf{B} + \mathbf{abs}_i \sum_{j \neq i}^n w_{ij} X_t \theta + \gamma_1 \sum_{j \neq i}^n w_{ij} q_{jt-1} + \gamma_2 \mathbf{abs}_i \sum_{j \neq i}^n w_{ij} R_{jt} + \varepsilon_{it}$$
(10)

⁸ Following Aghion and Howitt (1998), and Ertur and Koch (2011), we improve the productivity from horizontal innovation to vertical innovation.

⁹ The main element behind the convergence result in the neoclassical spatial model is also diminishing returns to reproducible capital. Physical capital externalities and technological interdependence only slow down the decrease in marginal productivity of physical capital. We develop a specification that explicitly includes the technological interdependence and spatial externalities. The result obtained from this section supports the convergence hypothesis in the Schumpeterian technology diffusion model. The growth rate of production per worker in country 2 can be expressed in the following DSDM for the Schumpeterian technology diffusion model (CAP model): If empirical results reject the null hypothesis, (H₀ : $\beta_1 = 0$), convergence hypotheses are accepted.

where X_t presents a matrix of explanatory variables including technology transfer. In this paper, we consider general interaction patterns with the complete structure of interaction between countries. The leading country diffuses a technology to Asian countries through the gap of TFP. According to the distance weight, technology diffusion is considered only among Asian countries.¹⁰ After considering the spatial independence among countries, we rewrite Eq. (10) in the DSDM matrix form for the Schumpeterian technological diffusion model:

$$R_t = \delta W R_t + Z_t \beta + W Z_t \theta + \mu + \xi_t I_N + \varepsilon_t \tag{11}$$

where Z is a matrix of explanatory variables (q_{t-1}) the initial relative income, s_{kt} logarithm of rate of physical capital, gap_{it} the technology gap, and abs_{it}: capacity of absorption). The rate of growth in the neighboring countries also reflects the spatial autocorrelation process implied by technological interdependence. To investigate the null hypothesis that the individual fixed effect and time-period fixed effects are jointly nonsignificant, we perform a likelihood ratio (LR) test. To test whether the spatial lag model or the spatial error model is a more appropriate description of the data than a model without any spatial interaction effects, one may use Lagrange multiplier (LM) tests for a spatially lagged dependent variable and for spatial error autocorrelation, as well as the robust LM tests which test for the existence of one type of spatial dependence conditional on the other (Elhorst 2014). The standard LM tests for spatial dependence in linear and panel regressions are derived under the normality and homoskedasticity assumptions of the regression disturbances. Baltagi and Yang (2013) introduce general methods to modify the standard LM tests such that they become robust against heteroskedasticity and nonnormality. The idea behind the robustification is to decompose the concentrated score function into a sum of uncorrelated terms so that the outer product of gradient can be used to estimate its variance.

The first hypothesis ($H_0: \theta = 0$) examines whether the SDM can be simplified to the SAM, and the second hypothesis ($H_0: \theta + \delta\beta = 0$) whether it can be simplified to the SEM.¹¹ These hypothesis can be assessed with either an LR test or a Wald test. If both hypotheses ($H_0: \theta = 0$ and $H_0: \theta + \delta\beta = 0$) are rejected, the SDM best describes the data. Conversely, if the first hypothesis cannot be rejected, then the SAM best describes the data, provided that the (robust) LM tests also support the SAM. Similarly, if the second hypothesis cannot be rejected, then the

¹⁰ Ertur and Koch (2011) consider some interaction patterns between countries, which may be incorporated in the W matrix. They first consider the case where there is a technological leader that diffuses its knowledge to other countries. The matrix of interactions is then defined as follows: $W = \begin{pmatrix} 0 & W_{12} \\ 0 & 0 \end{pmatrix}$. Only the last column representing the diffusion from the leader country to other countries has non null terms. There is no feedback effect from technological followers to the technological leader.

¹¹ The spatial econometrics literature is divided about whether to apply the specific-to-general (Stge) approach or the general-to-specific (Gets) approach (Florax et al. 2003; Mur and Angulo 2009). In the spatial model context, Florax et al., and Mur and Angulo suggest that the Gets strategy is superior to the Stge strategy. Indeed, one of the advantages of the Gets strategy identified by Mur and Angulo was that it was much more robust to heteroskedastic, skewed or heavy-tailed disturbances than the competitor Stge strategy. See LeSage and Pace (2009, p. 53), Elhorst (2010), and Burridge(2011).

spatial error model best describes the data, provided that the (robust) LM tests also pointed to the spatial error model. If one of these conditions is not satisfied, i.e., if the (robust) LM tests point to another model than the Wald/LR tests, then the spatial Durbin model should be adopted. This is because this model generalizes both the spatial lag and the spatial error model. Elhorst (2014) shows that the matrix of marginal effects of the expected value of the dependent variables with respect to the *k*th explanatory variable is given by the $N \times N$ matrix,

$$\left[\frac{\partial E(R_t)}{\partial z_{1k}}\cdots\frac{\partial E(R_t)}{\partial z_{Nk}}\right] = (1-\delta W)^{-1} [\beta_k + \theta_k W]$$
(12)

Lesage and Pace (2009) note that interpretation of the estimates can be misleading and advocate decomposing the marginal effects into the direct and indirect effects. The differences between the direct effects and the coefficient estimates are due to feedback effects that arise as a result of impacts passing through neighboring countries and back to the countries themselves. LeSage and Pace define the direct effect as the average of the diagonal elements of the matrix on the right-hand side of (12), and the indirect effect as the average of either the row sums or the column sums of the nondiagonal elements of that matrix and as a summary indicator of the spillover effect.

3.2 DSDM for the extended neoclassical growth model (NEO model)

In the previous section, we set up the Schumpeterian technology diffusion model assuming that the level of technology $A_t = \theta_t A$ is random, and $\ln \theta_t$ evolves according to an autoregressive process with random innovation, ε_t . Now, we examine the extended MRW exogenous growth model, which supports the convergence hypothesis. In the neoclassical growth model with the labor augmented technological progress ($A_t = A_0 e^{gt}$), the equation for the growth rate of output per worker seems similar to Eq. (7). However, the differences are that γ_1 is replaced by the rate of exogenous technical change, denoted by $g; \frac{y_2}{y_1}$ is replaced by \hat{y} , the country's output per effective worker; and $\left(\frac{y_2}{y_1}\right)^*$ is replaced by \hat{y}^* , the steady state level of output per effective worker. The neoclassical growth formula in the standard empirical model can be written as

$$\gamma_2 = \frac{\dot{y}_2}{y_2} = g + \Psi[\hat{y}, \hat{y}^*], \tag{13}$$

where the partial derivatives of the function Ψ satisfy $\Psi_1 < 0$ and $\Psi_2 > 0$, and $\Psi(\cdot, \cdot) = 0$ if $\hat{y} = \hat{y}^*$. The value \hat{y}^* depends on elements included in the parameter A, such as government policies, and on willingness to save. Higher values of A lead to increases in \hat{y}^* . The parameter g is not directly observable and varies over time and across countries. The key aspect of Eq. (13) involves the absolute levels of term $\Psi(\cdot)$, whereas Eq. (7) shows that growth rate depends on a country's characteristics expressed relative to those in the leader country.

We assume that aggregate level technology in region *i*, A_{it} may not only depend on externalities generated by physical and human capital accumulated in that region, but also on the aggregate level of technology of its neighboring economies, A_{jt} with $i \neq j$. In line with Ertur and Koch (2007) and Fischer (2011, 2018), we assume the following form for the level of technology in region *i* at time *t*, $A_{it} = \Omega_t k_{it}^{\phi_K} h_{it}^{\phi_H} \prod_{j\neq i}^n (A_{jt})^{\rho W_{ij}}$ where Ω_t represents some amount of technological knowledge, A_{jt} is the aggregate level of technology for region *j*, k_{it} is the per worker physical capital, and h_{it} is the per worker human capital. The technical parameters ϕ_K with $0 \le \phi_K < 1$ and ϕ_H with $0 \le \phi_H < 1$ reflect the spatial connectivity of k_{it} and h_{it} within country *i*, respectively. Each region has differentiated access to foreign technology because of the connectivity terms, denoted by W_{ij} . Under this assumption, the spatial extension model can be derived from the basic MRW model:

$$\ln\left(\frac{y_{it}}{y_{it-1}}\right) = \beta_0 + \beta_1 \ln y_{it-1} + \beta_2 \ln s_{kit} + \beta_3 \ln s_{hit} + \beta_4 \ln(n_{it} + g + \delta) + \theta_1 \sum_{j \neq i}^N w_{ij} \ln y_{jt-1} + \theta_2 \sum_{j \neq i}^N w_{ij} \ln s_{kjt} + \theta_3 \sum_{j \neq i}^N w_{ij} \ln s_{hjt} , \quad (14) + \theta_4 \sum_{j \neq i}^N w_{ij} \ln(n_{it} + g + \delta) + \rho \sum_{j \neq i}^N w_{ij} \ln\left(\frac{y_{jt}}{y_{jt-1}}\right) + \varepsilon_{it}$$

The growth rate of income per worker is negative function of the initial level of income per worker reflecting the convergence process with $\beta_1 < 0$ and depends positively on savings in physical and human capital with $\beta_2 > 0$ and $\beta_3 > 0$. The economic growth depends negatively on the effective rate of the capital depreciation rate $(n_{it} + g + \delta)$ with $\beta_4 < 0$. In the same direction, it also depends on the saving in physical and human capital in the neighboring economies and negatively on their effective rate of capital depreciation rate. The growth rate depends positively on the initial level of income per capita in the neighboring economies. The rate of growth in the neighboring countries also reflects the spatial autocorrelation process implied by technological interdependence. After considering the spatial interdependence among countries, we rewrite Eq. (14) in DSDM matrix form for the extended MRW model:

$$Y_t = \delta W Y_t + X_t \beta + W X_t \theta + e \tag{15}$$

where Y_t is the growth rate of income per worker along the balanced-growth path, W is a weight matrix based on coordinates, and $e = [\mu_i, \xi_t, \varepsilon_{it}]$.¹² We consider the extended MRW model including the other possibly time-varying variables affecting

¹² We calculate the standardized weight matrix by estimating the distance between each country's capital, expressed as latitude and longitude. Lesage and Pace (2009) and Elhorst (2012, 2014) provide the MATLAB program.

growth, which are FDI, the technology gap, and trade. Therefore, the explanatory variable vector, $X = [y_{t-1}, s_{kt}, n_t, s_{ht}, fdi_t, gap_t, trd_t]$, is presented.

The approach Lee and Yu (2016) proposed to obtain consistent results is a bias correction procedure of the parameters estimates obtained by the direct approach based on maximizing the likelihood function. This paper adopts the bias correction procedure when spatial fixed effects are controlled for, and time-period fixed effects are included.

4 Empirical results of the dynamic spatial Durbin panel model

4.1 Data

We consider data for the following 11 Asian countries over the period 1970–2014: China, Hong Kong, Indonesia, India, Korea, Malaysia, Philippines, Singapore, Sri Lanka, Thailand, and Taiwan.¹³ We consider the USA as a leader country to observe the effects of the influence of technological innovation on the 11 Asian countries. Data for real income per capita, the physical capital, human capital investment share of GDP, and population growth rate are drawn from the Penn World Table 9.0 (Feenstra et al. 2015). Real income per capita is obtained by dividing real GDP at constant 2011 national prices in millions of US dollars by population in millions. Growth rate is based on average annual income growth rate during the time period. The relative income represents $q_{it} = \ln(GDP_{it}/GDP_{USAt})$, where GDP_{it} is the real per worker GDP of Asian country i and GDP_{USAt} is the real per worker GDP of the leader country, the USA. A human capital index was estimated using data regarding average years of schooling from Barro and Lee (2013) and rates of return on education from Psacharopoulos and Patrinos (2004). Physical capital is obtained as the share of gross capital formation at current PPPs and export ratio as the share of merchandise exports at current PPPs. Exports by a follower country to leader countries facilitate the absorption of superior technologies from leaders. The increase in trade occurs due to product quality improvement and technological innovation in response to the demands of the importing country. FDI data are obtained by U.S. direct investment in Asian countries using balance of payments and direct investment position data obtained from the Bureau of Economic Analysis. As several empirical studies mention the importance of distinguishing the technology diffusion effects and productivity effects, we use both the ratios of FDI/physical capital and FDI/GDP in Asian countries.¹⁴ The TFP level in an Asian country at current purchasing power parity

¹³ U.S. direct investment data in Asian countries from Bureau of Economic Analysis (2017) has been available since 1970. There is no TFP data for Bangladesh and Pakistan in the PWT 9.0.

¹⁴ Benhabib et al. (2014, 2017) examine how innovation and technology diffusion interact to endogenously determine the productivity distribution and generate aggregate growth. They model firms that choose to innovate, adopt technology, or produce with their existing technology. Whether and how innovation and diffusion contribute to aggregate growth depends on the support of the productivity distribution.

	•••		
	Spatial fixed effect	Time fixed effect	Spatial fixed and time fixed effect
LM test: no spatial lag	1.59 (0.20)	7.63 (0.0)***	7.56 (0.00)***
Robust LM test: no spatial lag	5.51 (0.01)**	0.41 (0.50)	0.40 (0.52)
LM test: no spatial error	6.14 (0.01)**	9.64 (0.00)***	9.54 (0.00)***
Robust LM test: no spatial error	10.07 (0.00)***	2.42 (0.11)	2.39 (0.12)

 Table 2
 LM test of for neoclassical technology diffusion model (NEO model)

(1) Significance level in parentheses. (2) ***, and **denote significance at 1%, 5% levels, respectively

 Table 3
 LR and Wald tests for neoclassical technology diffusion model (NEO model)

Wald test spatial lag	LR test spatial lag	Wald test spatial error	LR test spatial error
36.72*** (0.00)	43.33*** (0.00)	37.12*** (0.00)	42.12*** (0.00)

(1) Significance level in parentheses. (2) *** denotes significance at 1% level

(PPP) at USA = 1 is obtained. We use a weight matrix W based on coordinates (distance from latitude and longitude), where W is row-standardized.¹⁵

4.2 Results for extended neoclassical growth model

Now, we test Eq. (15) for extended neoclassical growth model (NEO model) allowing spatial interdependence among 11 Asian countries to test the convergence hypothesis. To investigate the null hypothesis that the individual fixed effect and time-period fixed effects are jointly insignificant, we perform a likelihood ratio (LR) test. The LR test for joint insignificance of the individual fixed effects at income per capita is not rejected at 10% level (1.882, with 11 degrees, of freedom, p=0.998). Conversely, the LR test for the joint insignificance of the time-period fixed effects is rejected at the 1% level (144.8, with 45 degrees, of freedom, p=0.00). Based on these results, we include the time-period effects in the tested model. Table 2 reports our estimation results to determine whether the SAM or the SEM is more appropriate when we adopt a nonspatial panel data model. Provided that time-period fixed effects or both individual and time-period fixed effects are included, the classical LM tests of the hypothesis of no spatially lagged dependent variable term can be rejected only at 1 percent significance and 5 percent significance, respectively. Provided that individual fixed effects are included, both the hypothesis of no spatially lagged dependent variable and the hypothesis of no spatial autocorrelated error term can be rejected when using robust LM tests.

¹⁵ Lee and Yu (2016) report the results with matrices constructed geographical distance and with weighs from bilateral trade flow. Ditzen (2018) uses spatial weights matrices, trade shares, foreign direct investments, and the shares of high-skilled migrants.

Since the nonspatial model is rejected based on the results of Table 2, we estimate the spatial Durbin specification for Asian countries to test whether it can be simplified to the SAM or the SEM (general-to-specific approach), as shown in Table 3. We perform the Wald and LR tests to determine whether the SDM can be simplified to the SAM. The results of the Wald test (36.72, p=0.00) and LR test (43.33, p=0.00) indicate that the hypothesis can be rejected. Similarly, the hypothesis that the SDM can be simplified to the SEM cannot be rejected using a Wald test (37.12, p=0.00) or an LR test (42.12, p=0.00). This result indicates that SDM is the most appropriate specification for the relationship.

The results for the estimated coefficients containing spatially lagged dependent variables of the spatial Durbin model are reported in Table 4. The Hausman test can be used to test whether the random effects model is more appropriate than the fixed effects model. Our results (58.17, p < 0.01) for per capita income indicate that the random effects model must be rejected. The estimated coefficient for the spatially lagged dependent variables ($W \times dep.var$) is 0.419 (p=0.00), which is positive and significant. The results show that the income growth rate is influenced by per capita incomes in neighboring location countries as well.

Provided that individual fixed effects, time-period fixed effects or both individual and time-period fixed effects are included, the coefficient for the initial per capita income is $-0.089 \ (p=0.00), -0.085 \ (p=0.00), \text{and} -0.125 \ (p=0.00), \text{respectively}, which are negative and significant. Following LeSage and Pace (2009), we estimate direct and indirect effects to yield an interpretation of the spatial spillover effects. We first consider the SDM with individual fixed effects. The direct effect of initial income is estimated to be <math>-0.094$ at a significance level below 1%. The statistically significant indirect effect is -0.059. The total effect is thus -0.154, which is significant below the 1% level. The total effect of these feedback sources is greater than when we consider only the direct effect.

We focus on a model with both individual and time-period fixed effects. The estimates of direct, indirect, and total effect of initial income are -0.119 (p=0.00), -0.108 (p=0.00), and -0.227 (p=0.00), respectively, which are significant and negative at a level below 1%. These results support the conditional convergence hypothesis for per capita incomes in the 11 Asian developing countries. All of them are much larger than results presented in the previous literature. Elhorst et al. (2010) also pointed out that the use of the fixed effect panel model generates a higher convergence rate.

The coefficients 0.034 (p=0.00) and 0.292 (p=0.00) of the physical investment rate and human capital investment rate, respectively, on the growth of per capita income are positive, as predicted, and are significant. However, the coefficient of population growth on the growth of per capita income is also positive, which is not predicted by theory and is not significant. The coefficient of TFP is 0.246 at a significant level below 1%. The coefficients of FDI and export over GDP are 0.018 and 0.056 below 5% and 1%, respectively. When we compare the total effects of the estimated variables, the coefficient (0.343, p=0.00) of TFP is greater at 1% than the coefficient (0.356, p=0.12) of human capital, which is not significant at a level of 10% or greater. We find that the total effects of human capital investment rate, total factor productivity, and trade on relative income growth are positive and significant.

	Individual fixed effects	Time-period fixed effects	Individual and time- period fixed effects
$\ln y_{t-1}$	-0.089 (0.00)***	-0.085 (0.00)***	-0.125 (0.00)***
$\ln s_k$	0.046 (0.00)***	0.055 (0.00)***	0.034 (0.00)***
$\ln(n + 0.05)$	-0.055 (0.02)**	-0.066 (0.02)**	0.019 (0.42)
$\ln s_h$	0.273 (0.00)***	0.155 (0.00)***	0.292 (0.00)***
ln gap	0.208 (0.00)***	0.189 (0.00)***	0.246 (0.00)***
ln fdi	0.007 (0.17)	-0.001 (0.71)	0.018 (0.01)**
ln trd	0.022 (0.07)*	0.043 (0.00)***	0.056 (0.00)***
$W \times \ln y_{t-1}$	0.001 (0.95)	-0.045 (0.09)*	-0.149 (0.00)***
$W \times \ln s_k$	-0.030 (0.01)**	-0.002 (0.87)	-0.017 (0.31)
$W \times \ln(n + 0.05)$	0.010 (0.85)	0.095 (0.00)***	-0.192 (0.00)***
$W \times \ln s_h$	0.215 (0.10)	0.105 (0.33)	0.137 (0.52)
$W \times \ln gap$	-0.018 (0.72)	0.043 (0.53)	0.167 (0.01)**
$W \times \ln f di$	0.003 (0.76)	0.003 (0.73)	0.012 (0.44)
$W \times \ln trd$	-0.005 (0.80)	0.009 (0.64)	0.096 (0.00)***
$W \times dep.var$	0.419 (0.00)***	-0.119 (0.06)*	-0.209 (0.00)***
Direct effect $\ln y_{t-1}$	-0.094 (0.00)***	-0.084 (0.00)***	-0.119 (0.00)***
Indirect effect $\ln y_{t-1}$	-0.059 (0.10)	-0.032 (0.19)	-0.108 (0.00)***
Total effect $\ln y_{t-1}$	-0.154 (0.00)***	-0.117 (0.00)***	-0.227 (0.00)***
Direct effect $\ln s_k$	0.044 (0.00)***	0.056 (0.00)***	0.035 (0.00)***
Indirect effect $\ln s_k$	-0.016 (0.45)	-0.008 (0.58)	-0.021 (0.17)
Total effect $\ln s_k$	0.028 (0.26)	0.049 (0.01)**	0.014 (0.41)
Direct effect $\ln(n + 0.05)$	-0.057 (0.06)	$-0.070 (0.00)^{***}$	0.010 (0.64)
Indirect effect $\ln(n + 0.05)$	-0.019 (0.83)	0.096 (0.03)**	0.166 (0.00)***
Total effect $\ln(n + 0.05)$	-0.077 (0.50)	0.026 (0.49)	0.176 (0.00)***
Direct effect $\ln s_h$	0.315 (0.00)***	0.153 (0.00)***	0.284 (0.00)***
Indirect effect $\ln s_h$	0.054 (0.02)**	0.081 (0.41)	0.072 (0.70)
Total effect $\ln s_h$	0.855 (0.00)***	0.234 (0.05)*	0.356 (0.12)
Direct effect ln gap	0.213 (0.00)***	0.189 (0.00)***	0.240 (0.00)***
Indirect effect ln gap	0.113 (0.20)	0.020 (0.73)	0.102 (0.10)
Total effect ln gap	0.330 (0.00)***	0.210 (0.01)**	0.343 (0.00)***
Direct effect ln fdi	0.001 (0.19)	-0.001 (0.69)	0.017 (0.00)***
Indirect effect ln fdi	0.001 (0.60)	0.002 (0.77)	0.007 (0.60)
Total effect ln <i>fdi</i>	0.017 (0.43)	0.001 (0.86)	0.025 (0.16)
Direct effect ln trd	0.002 (0.12)	0.042 (0.00)***	0.051 (0.00)***
Indirect effect ln trd	0.005 (0.88)	0.004 (0.81)	0.075 (0.01)**
Total effect ln <i>trd</i>	0.027 (0.52)	0.047 (0.04)**	0.126 (0.00)***
R^2	0.44	0.52	0.59
σ^2	0.001	0.001	0.001
Log likelihood	1050.8	1092.6	1133.0
Hausman test	58.17 (0.00)***		

 Table 4
 Estimation results for neoclassical technology diffusion model (NEO model)

(1) Dependent variable: $\ln (y_{it}/y_{it-1})$ where y_{it} is per capita income of follower country *i*. (2) Hausman test: probability < 0.01 implies rejection of spatial random effects. (3) Significance level is given in parentheses. (4) ***, **, and * denote significance at 1%, 5%, 10% levels, respectively. (5) *W*: Weight due to the geographical distance between region *i* and *j*. (6) Number of observations: 495

GAP models	Wald test spatial lag	LR test spatial lag	Wald test spatial error	LR test spatial error
GAP(1)	59.23*** (0.00)	54.01*** (0.00)	56.13*** (0.00)	52.49*** (0.00)
GAP(2)	74.98*** (0.00)	66.40*** (0.00)	71.64*** (0.00)	65.41*** (0.00)
GAP(3)	59.75*** (0.00)	54.30** (0.00)	56.84*** (0.00)	53.01*** (0.00)
GAP(4)	86.22*** (0.00)	75.14*** (0.00)	81.12*** (0.00)	73.39*** (0.00)

 Table 5
 Likelihood Ratio and Wald tests for spatial dependence (GAP model)

(1) Each model includes a variable of technology absorption capability such as $(fdi \times s_h)$ at GAP(1), $(fdi \times gap)$ at GAP(2), $(trd \times s_h)$ at GAP(3), and $(trd \times gap)$ at GAP(4). (2) Significance level in parentheses. (3) *** denotes significance at 1% level

4.3 Results for Schumpeterian technology diffusion model

We first follow the previous research determining that the technology shock of the leader country is transmitted through FDI or trade.¹⁶ Therefore, we incorporate variables to include the international transfer of technology into the diffusion model discussed above. We then test whether technology is transmitted either by FDI (*fdi*) or by international trade (*trd*) and whether the transmission is sped up by the human capital (*s_h*) or TFP (gap). After allowing spatial interdependence among Asian countries, we can write DSDM matrix form for the growth rate equation of relative income (*GAP model*)¹⁷:

$$R_t = \delta W R_t + Z_t \beta + W Z_t \theta + e \tag{16}$$

where the explanatory variable matrix, $Z = [q_{t-1}, s_k, s_h, gap, trd, fdi, (fdi \times s_h), (fdi \times gap), (trd \times s_h), (trd \times gap)]$. Since the nonspatial model is rejected by classical (robust) LM tests, we estimate the spatial Durbin specification *GAP* models in order to test whether it can be simplified to the SAM or the SEM, as presented in Table 5. The hypothesis that the SDM can be simplified to the SAM or the SEM is not rejected by a Wald test or LR test. This indicates that SDM is the most appropriate specification for the relationship.

The results of the Hausman test indicate that the random effects model must be rejected. We do not report the results of models with individual fixed or time fixed effects to save space. We focus on a model with both individual and time-period fixed effects. For the same reason, we present only the total effects of the estimation results including the direct and indirect effect of explanatory variables. Each model includes a variable of technology transfer channel such as $(fdi \times s_h)$ at the GAP(1), $(fdi \times gap)$ at the GAP(2), $(trd \times s_h)$ at the GAP(3), and $(trd \times gap)$ at the GAP(4). Estimated coefficients for the lagged relative income q_{t-1} are significant and negative at a level below 1%, respectively, and indicate convergence among Asian countries. The negative and significant coefficients for spatially lagged relative income imply that regional economies are disadvantaged by income growth in neighboring countries. In other words, relative income in

¹⁶ See Carkovic and Levine (2002), Kim (2008), Wu and Hsu (2008), Felipe and McCombie (2017).

¹⁷ After allowing spatial interdependence among Asian countries, we assume the level of technology in region *i* at time *t*, $g_{it} = \frac{A_{it}}{A_{ir}} = \lambda \sigma k_{it}^{\omega} h_{it}^{e} \prod_{j=1}^{n} \left(\frac{A_{jt}}{A_{ir}}\right)^{r_i v_{ij}}$.

a given country is negatively associated with income in the surrounding countries. The total effect of the human capital investment rate, TFP, and trade on the growth of relative income is positive and significant in the *GAP* models. However, the coefficients of other explanatory variables ($W \ln s_k$, $W \ln fdi$, $W(\ln fdi \times \ln s_h)$), $W(\ln fdi \times \ln gap)$, $W(\ln trd \times \ln s_h)$) on the growth of relative income are not strong enough to reject the null hypothesis. The total effect (0.310, p = 0.00) of the technology transfer channel ($trd \times gap$) at the *GAP*(4) is significant at a level below 1%, and ($fdi \times gap$) at the *GAP*(2) is only significant at a level below 5%, respectively (Table 6).

Now, we test the convergence hypothesis for the Schumpeterian technology diffusion model (*CAP model*) among 11 Asian countries. New technologies which are considered to be a technical shock (the ratio of TFP, *gap*) coming from leading country are diffused through a variety of channels. Growth rate (R_t) depends positively on the initial relative income (q_{t-1}), the ratio of technology shock (*gap*), and the absorption capacity in the neighboring economies. We test how this shock of technology is transferred in combination with the absorption capacity of the Asian country, physical capital (s_k), human capital (s_h), FDI (*fdi*), and trade (*trd*), among other factors. After allowing spatial interdependence among Asian countries, we can rewrite Eq. (11) in DSDM matrix form:

$$R_t = \delta W R_t + Z_t \beta + W Z_t \theta + e \tag{17}$$

where the explanatory variable matrix, $Z = [q_{t-1}, gap, (gap \times s_k), (gap \times s_h), (gap \times fdi), (gap \times fdi(1)), (gap \times trd)], fdi$ represents FDI/physical capital, and fdi(1) represents FDI/GDP. W is a weight matrix based on coordinate and $e = [\mu_i, \xi_t, \epsilon_{it}]$.

To investigate the null hypothesis that the individual fixed effect and time-period fixed effects are jointly insignificant, we perform a likelihood ratio (LR) test. The LR test for joint insignificance of the individual fixed effects at income per capita is rejected at the 1% level. Based on these results, we include the individual and time-period fixed effects in the tested model. Provided that both individual and time-period fixed effects are included, the classical (robust) LM tests of the hypothesis of no spatially lagged dependent variable term can be rejected only at 1 percent significance. We did not present these results of LR and LM test for space limit.

Since the nonspatial model is rejected, we estimate the spatial Durbin to test whether it can be simplified to the SAM or the SEM as shown in Table 7. We perform the Wald and LR tests to determine whether the SDM can be simplified to the SAM or the SDM can be simplified to the SEM. The results of the Wald and LR tests for all *CAP* models indicate that the both hypothesis can be rejected. These findings indicate that SDM is the most appropriate specification for the relationship.¹⁸

We focus on a model with both individual and time-period fixed effects to save space. For the same reason, only total effects, excluding the direct effect and indirect

¹⁸ These results suggest that the absorption capacity of technology transfer plays an important role in the growth and development process and is consistent with our Schumpeterian technological diffusion model.

	GAP(1)	GAP(2)	GAP(3)	GAP(4)
q_{it-1}	-0.132 (0.00)***	-0.165 (0.00)***	-0.160 (0.00)***	-0.171 (0.00)***
$\ln s_k$	0.011 (0.00)***	0.021 (0.00)***	0.016 (0.00)***	0.024 (0.00)***
ln s _h	0.156 (0.01)**	0.332 (0.00)***	0.249 (0.00)***	0.381 (0.00)***
ln gap	0.150 (0.00)***	0.370 (0.00)***	0.170 (0.00)***	0.251 (0.00)***
ln <i>fdi</i>	0.013 (0.00)***	0.039 (0.00)***	0.009 (0.01)**	0.008 (0.02)**
ln trd	-0.016 (0.01)**	-0.006 (0.34)	-0.026 (0.01)**	0.012 (0.22)
$(\ln fdi \times \ln s_h)$	-0.025 (0.07)*	_	_	_
$(\ln fdi \times \ln gap)$	_	0.065 (0.00)***	_	_
$(\ln trd \times \ln s_h)$	_	_	0.031 (0.17)	_
$(\ln trd \times \ln gap)$	_	_	_	0.086 (0.00)***
Wq_{it-1}	-0.181 (0.00)***	-0.228 (0.00)***	-0.209 (0.00)***	-0.287 (0.00)***
$W \ln s_k$	-0.016 (0.12)	-0.009 (0.34)	-0.011 (0.28)	-0.016 (0.12)
$W \ln s_h$	0.362 (0.03)**	0.769 (0.00)***	0.504 (0.01)**	0.362 (0.03)**
W ln gap	0.162 (0.00)***	0.255 (0.02)**	0.186 (0.00)***	0.162 (0.00)***
W ln fdi	0.009 (0.36)	0.022 (0.11)	0.009 (0.35)	0.009 (0.36)
W ln trd	-0.074 (0.00)***	-0.056 (0.00)***	-0.097 (0.00)***	-0.074 (0.00)***
$W(\ln fdi \times \ln s_h)$	-0.025 (0.56)	_	_	_
$W(\ln fdi \times \ln gap)$	_	0.017 (0.53)	_	_
$W(\ln trd \times \ln s_h)$	_	_	0.069 (0.36)	_
$W(\ln trd \times \ln gap)$	_	_	_	0.285 (0.00)***
Wdep.var	-0.163 (0.01)**	-0.171 (0.00)***	-0.159 (0.01)**	-0.210 (0.00)***
Total effect				
q_{it-1}	-0.270 (0.00)***	-0.331 (0.00)***	-0.318 (0.00)***	-0.381 (0.00)***
$\ln s_k$	-0.003 (0.74)	0.010 (0.34)	0.004 (0.74)	0.029 (0.03)**
$\ln s_h$	0.433 (0.02)**	0.938 (0.00)***	0.643 (0.00)***	1.070 (0.00)***
ln gap	0.269 (0.00)***	0.532 (0.00)***	0.2306 (0.00)***	0.592 (0.00)***
ln <i>fdi</i>	0.019 (0.11)	0.052 (0.00)***	0.016 (0.16)	0.011 (0.28)
ln trd	-0.079 (0.00)***	-0.054 (0.00)***	-0.107 (0.00)***	0.042 (0.20)
$(\ln fdi \times \ln s_h)$	-0.044 (0.29)	_	_	_
$(\ln fdi \times \ln gap)$	_	0.071 (0.03)**	_	_
$(\ln trd \times \ln s_h)$	_	_	0.084 (0.27)	_
$(\ln trd \times \ln gap)$	_	_	_	0.310 (0.00)***
R^2	0.56	0.59	0.56	0.58
σ^2	0.0002	0.0002	0.0002	0.0002
Log likelihood	1365.1	1382.8	1364.5	1375.8
Hausman test	51.77 (0.00)***	54.76 (0.00)***	56.77 (0.00)***	64.26 (0.00)***

 Table 6
 Estimation results for Schumpeterian technology diffusion model (GAP model)

(1) Dependent variable: $R_{it} = q_{it} - q_{it-1}$ where $q_{it} = \ln(y_{it}/y_{1t})$, and y_{it} and y_{1t} are per capita income of an Asian country and leader country, respectively. (2) Technology absorption capability such as ($fdi \times s_h$) at GAP(1), ($fdi \times gap$) at GAP(2), ($trd \times s_h$) at GAP(3), and ($trd \times gap$) at GAP(4) model. (3) Hausman test: probability <0.01 implies rejection of spatial random effects. (4) Significance level is given in parentheses. (5) ***, **, and * denote significance at 1%, 5%, 10% levels, respectively. (6) W: Weight due to the geographical distance between regions *i* and *j*. (7) *GAP models* focus on a model with both individual and time-period fixed effects. (8) Number of observations: 495

CAP Models	Wald test spatial lag	LR test spatial lag	Wald test spatial error	LR test spatial error
CAP(1)	72.23*** (0.00)	66.28*** (0.00)	71.64*** (0.00)	66.17*** (0.00)
CAP(2)	70.10*** (0.00)	64.62*** (0.00)	69.31*** (0.00)	64.38*** (0.00)
CAP(3)	49.71*** (0.00)	47.09*** (0.00)	49.30*** (0.00)	46.99*** (0.00)

Table 7 LR and Wald tests for Schumpeterian technology diffusion model (CAP model)

(1) Significance level in parentheses. (2) *** denotes significance at 1% level

 Table 8 Estimation results for Schumpeterian technology diffusion model (CAP model)

	CAP(1)	CAP(2)	CAP(3)
q_{it-1}	-0.121 (0.00)***	-0.122 (0.00)***	-0.127 (0.00)***
ln gap	0.137 (0.00)***	0.90 (0.09)*	_
$\ln gap \times \ln s_k$	-0.055 (0.00)***	-0.055 (0.00)***	-0.076 (0.00)***
$\ln gap \times \ln s_h$	-0.043 (0.56)	-0.033 (0.56)	-0.001 (0.87)
$\ln gap \times \ln fdi$	0.008 (0.25)	-	_
$\ln gap \times \ln fdi(1)$	-	-0.003 (0.55)	-0.008 (0.06)*
$\ln gap \times \ln trd$	0.023 (0.20)	0.037 (0.01)**	0.027 (0.07)*
$W \times q_{it-1}$	-0.103 (0.00)***	-0.091 (0.01)**	-0.038 (0.29)
$W \times \ln gap$	0.702 (0.00)***	0.585 (0.00)***	_
$W \times (\ln gap * \ln s_k)$	0.094 (0.00)***	0.085 (0.00)***	0.020 (0.43)
$W \times (\ln gap * \ln s_h)$	-0.923 (0.00)***	-0.938 (0.00)***	-0.492 (0.00)***
$W \times (\ln gap * \ln fdi)$	0.009 (0.62)	-	_
$W \times (\ln gap * \ln fdi(1))$	-	-0.012 (0.42)	-0.051 (0.00)***
$W \times (\ln gap * \ln trd)$	0.172 (0.00)***	0.192 (0.00)***	0.207 (0.00)***
$W \times dep.var$	-0.096 (0.13)	-0.099 (0.12)	-0.056 (0.37)
Total effect:			
q_{it-1}	-0.205 (0.00)***	-0.194 (0.00)***	-0.150 (0.00)***
ln gap	0.765 (0.00)***	0.614 (0.00)***	_
$\ln gap \times \ln s_k$	0.034 (0.34)	0.025 (0.48)	-0.052 (0.10)
$\ln gap \times \ln s_h$	-0.887 (0.00)***	-0.890 (0.00)***	-0.477 (0.02)**
$\ln gap \times \ln fdi$	0.016 (0.46)	_	_
$\ln gap \times \ln fdi(1)$	-	-0.013 (0.39)	-0.056 (0.00)***
$\ln gap \times \ln trd$	0.179 (0.00)***	0.210 (0.00)***	0.221 (0.00)***
R^2	0.56	0.56	0.54
σ^2	0.0002	0.0002	0.0002
Log likelihood	1367.5	1367.6	1358.5
Hausman test	54.25 (0.00)***	52.34 (0.00)***	142.98 (0.00)***

(1) Dependent variable: $R_{it} = q_{it} - q_{it-1}$ where $q_{it} = \ln(y_{it}/y_{1t})$, and y_{it} and y_{1t} are per capita income of an Asian country and leader country, respectively. (2) $\ln fdi$ represents FDI/physical capital, $\ln fdi(1)$ represents FDI/GDP. (3) Hausman test: probability < 0.01 implies rejection of spatial random effects. (4) Significance level is given in parentheses. (5) ***, **, and * denote significance at 1%, 5%, 10% levels, respectively. (6) *W*: Weight due to the geographical distance between regions *i* and *j*. (7) *CAP models* focus on a model with both individual and time-period fixed effects. (8) Number of observations: 495 effect of the estimated coefficients, are reported. The results for the estimated coefficients containing a spatially lagged dependent variables of spatial Durbin model are reported in Table 8. The Hausman test can be used to test whether the random effects model is more appropriate than the fixed effects model. Our results (54.25, p < 0.01) for the *CAP(1)* model, (52.34, p < 0.01) for the *CAP(2)* model, and (142.98, p < 0.01) for the *CAP(3)* model indicate that the random effects model must be rejected, respectively. The estimated coefficient for the spatially lagged dependent variables ($W \times dep.var$) is negative and insignificant. The results do not show that the relative income growth rate is influenced by per capita incomes in neighboring location countries as well.

Provided that both individual and time-period fixed effects are included, the coefficient for the initial relative income is -0.121 (p=0.00), -0.122 (p=0.00), and -0.1127 (p=0.00) for each *CAP* model, respectively, which are negative and significant. Following LeSage and Pace (2009), we estimate the direct and indirect effects to yield an interpretation of the spatial spillover effects. The estimates of total effect of initial relative income are -0.205 (p<0.01) for the *CAP(1)* model, -0.194 (p<0.01) for the *CAP(2)* model, and -0.150 (p<0.01) for the *CAP(3)* model which are significant and negative at a level below 1%, respectively. These results support the conditional convergence hypothesis among Asian countries.

The coefficients and total effects of absorption capacity, $gap \times s_k$ and $gap \times s_h$, are different from theoretical positive expected signs. One possible reason is that ratio of total factor productivity of the following country and leader country, technology gap (*gap*), is decreasing. Otherwise, the investment ratios of Asian countries are too high which may lead to the economies over-accumulated, then have a small negative effect on economic growth. The total effects of ln *gap* and *gap* × *trd* are positive and significant in all *CAP* models. However, the estimated coefficients of $gap \times s_k$, $gap \times s_h$, $gap \times fdi$, and $gap \times fdi(1)$ are either not significant or are negative. The shock of technology is transferred by absorption capacity in combination with trade in Asian countries.¹⁹ Therefore, Asian countries should further promote trade liberalization, a channel for technology transfer, and open more markets.

4.4 Results for extended EK12_NEO and EK12_CAP model

We consider Japan as a leader country to observe the effects of the influence of technological innovation and the convergence on the 11 Asian countries. The Japanese economy had greatly influenced the economic growth of Asian developing countries. Following the technology diffusion model, described in Ertur and Koch (2011), we include Japan among 11 Asian countries to see its influence on neighboring developing countries. We assume that not only does the technology leader spread knowledge to Asian countries, but also Asian countries contribute to technology diffusion

¹⁹ Buera and Oberfield (2016) provide a tractable theory of innovation and technology diffusion to explore the role of international trade in the process of development. Perla et al. (2016) study how opening to trade affects economic growth in a model where heterogeneous firms can choose to adopt a new technology already in use by other firms.

		<i>c.</i>	· —	,
	EK(1)	<i>EK</i> (2)	EK(3)	EK(4)
$\ln y_{t-1}$	-0.055 (0.00)***	-0.081 (0.00)***	-0.065 (0.00)***	-0.092 (0.00)***
$\ln s_k$	0.104 (0.00)***	0.120 (0.00)***	0.081 (0.00)***	0.102 (0.00)***
$\ln(n + 0.05)$	-0.067 (0.00)***	-0.018 (0.01)**	-0.057 (0.00)***	-0.063 (0.02)**
ln s _h	0.157 (0.00)***	0.410 (0.00)***	0.126 (0.06)*	0.297 (0.00)***
ln <i>fdi</i>	0.013 (0.00)***	_	-	0.195 (0.00)***
ln <i>tfp</i>	-	0.174 (0.00)***	-	0.012 (0.22)
ln trd	_	_	0.552 (0.00)***	0.398 (0.00)***
$W \times lny_{t-1}$	0.017 (0.36)	_	0.052 (0.17)	0.003 (0.84)
$W \times \ln s_k$	-0.027 (0.33)	_	0.017 (0.36)	-0.016 (0.03)**
$W \times \ln(n + 0.05)$	0.028 (0.85)	_	0.017 (0.75)	0.016 (0.78)
$W \times \ln s_h$	-0.051 (0.00)***	_	0.068 (0.54)	0.211 (0.08)*
$W \times \ln f di$	0.010 (0.26)	_	_	0.005 (0.54)
$W \times \ln t f p$	-	-	-	-0.036 (0.47)
$W \times \ln trd$	-	-	0.149 (0.60)	0.319 (0.30)
$W \times dep.var$	0.432 (0.00)***	0.395 (0.00)***	0.424 (0.00)***	0.438 (0.00)***
R^2	0.38	0.42	0.34	0.46
σ^2	0.001	0.001	0.001	0.001
Log likelihood	1014.5	1142.6	1008.0	1050.8
Hausman test	48.13 (0.00)***	47.74 (0.00)***	49.11 (0.00)***	40.87 (0.00)***
Number obs.	540	540	540	540
Spatial lag (Wald test)	36.80 (0.00)***	3.27 (0.65)	15.48 (0.00)***	36.16 (0.00)***
Spatial lag (LR test)	34.29 (0.00)***	3.25 (0.66)	14.73 (0.00)***	34.16 (0.00)***
Spatial error (Wald test)	35.33 (0.00)***	3.39 (0.64)	14.27 (0.00)***	34.88 (0.00)***
Spatial error (LR test)	33.57 (0.00)***	3.36 (0.64)	13.87 (0.00)***	33.62 (0.00)***

 Table 9
 Estimation results for neoclassical technology diffusion model (EK12_NEO model)

(1) Dependent variable: $Y_{it} = \ln y_{it} - \ln y_{it-1}$ where y_{it} are per capita income of an Asian country. (2) Hausman test: probability < 0.01 implies rejection of spatial random effects. (3) Significance level is given in parentheses. (4) ***, **, and * denote significance at 1%, 5%, 10% levels, respectively. (5) W: Weight due to the geographical distance between regions *i* and *j*. (6) *EK models* focus on a model with both individual and time-period fixed effects

to the leading country. There is a feedback effect from technological followers to the technological leader. We consider general interaction patterns with the complete structure of interaction between Asian countries. Therefore, we allow knowledge spillover and spatial interdependence among 12 Asian countries. According to the distance weight, technology diffusion is considered only among Asian countries.

We now consider data for the following 12 Asian countries over the period 1970–2014: China, Hong Kong, Indonesia, India, Japan, Korea, Malaysia, Philippines, Singapore, Sri Lanka, Thailand, and Taiwan. Data for empirical tests are also drawn from the Penn World Table 9.0 and the Bureau of Economic Analysis. Real income per capita is obtained at the constant 2011 national prices and growth rate is based on the average annual income growth rate during the time.

Now, we test the extended Ertur and Koch growth model (*EK12 NEO model* and *EK12 CAP model*) allowing spatial interdependence among 12 Asian countries to test the convergence hypothesis. This result indicates that SDM is the most appropriate specification for the relationship except the EK(2) including the explanatory variable, tfp. The results for the estimated coefficients containing spatially lagged dependent variables of the spatial Durbin model are reported in Table 9. The estimated coefficients for the spatially lagged dependent variables ($W \times dep.var$) are $0.432 \ (p = 0.00), \ 0.424 \ (p = 0.00)$ and $0.438 \ (p = 0.00)$ which are positive and significant, respectively. The results show that the income growth rate is also influenced by per capita incomes in neighboring location countries. Provided that both individual and time-period fixed effects be included, the coefficient for the initial per capita income is $-0.055 \ (p=0.00), -0.081 \ (p=0.00), and -0.092 \ (p=0.00), respectively,$ which are negative and significant at a level below 1%. These results support the conditional convergence hypothesis for per capita incomes in the 12 Asian countries. The coefficients of TFP, productivity, and trade which present technology diffusion channel are 0.013 (p=0.00), 0.174 (p=0.00) and 0.552 (p=0.00) at a significant level below 1%, respectively. As predicted from EK(4) model, the coefficients 0.102 (p=0.00) and 0.297 (p=0.00) of the physical investment rate and human capital investment rate, respectively, on the growth of per capita income are positive and significant.

We follow previous research which determined that the technology shock of the leader country is transmitted through FDI, productivity, or trade. We test whether technology is transmitted either by FDI (*fdi*), productivity (*tfp*), or by international trade (*trd*) and whether the transmission is sped up by human capital (s_h) . Each *EK* model includes a variable of a technology transfer channel such as $(fdi \times s_h)$ at the EK(5), $(tfp \times s_h)$ at the EK(6), and $(trd \times s_h)$ at the EK(7). The estimated coefficients for the spatially lagged dependent variables ($W \times dep.var$) are 0.397 (p = 0.00), 0.394 (p=0.00) and 0.402 (p=0.00) which are positive and significant, respectively. The results show that the income growth rate is also influenced by per capita incomes in neighboring location countries. The coefficients of absorption capacity, $(tfp \times s_h)$ at the EK(6), and $(trd \times s_h)$ at the EK(7) are positive and significant. However, the estimated coefficient of $(fdi \times s_h)$ at the EK(5) is insignificant and negative. The technology shock is transferred by absorption capacity in combination with trade or productivity in Asian countries. The coefficient for the initial per capita income is -0.030 (p=0.00), -0.025 (p=0.00), and -0.054 (p=0.00), respectively, which arenegative and significant at a level below 1%. These results support the conditional convergence hypothesis for per capita incomes in the 12 Asian countries. We find that Japanese technological progressive spillover to neighboring Asian countries and Japanese economy play a part in accelerating the convergence of Asian economies (Table 10).

0.001

540

1106.6

34.8 (0.00)***

	<i>EK</i> (5)	EK(6)	EK(7)
lny _{it-1}	-0.030 (0.00)***	-0.025 (0.00)***	-0.054 (0.00)***
ln s _k	0.101 (0.00)***	0.101 (0.00)***	0.105 (0.00)***
$\ln(n + 0.05)$	-0.092 (0.00)**	-0.095 (0.00)***	-0.087 (0.00)***
$(\ln fdi \times \ln s_h)$	-0.006 (0.39)	-	_
$(\ln tfp \times \ln s_h)$	_	0.311 (0.00)***	_
$(\ln trd \times \ln s_h)$	_	-	0.233 (0.00)***
$W \times dep.var$	0.397 (0.00)***	0.394 (0.00)***	0.402 (0.00)***
R^2	0.34	0.34	0.36

0.001

540

1106.8

41.3 (0.00)***

 Table 10 Estimation results for Schumpeterian technology diffusion model (EK12 CAP model)

(1) Dependent variable: $Y_{it} = \ln y_{it} - \ln y_{it-1}$ where y_{it} are per capita income of an Asian country. (2) Technology absorption capability such as $(fdi \times s_h)$ at EK(5), $(tfp \times s_h)$ at EK(6), and $(trd \times s_h)$ at EK(7)model. (3) Hausman test: probability < 0.01 implies rejection of spatial random effects. (4) Significance level is given in parentheses. (5) ***, and ** denote significance at 1%, 5% levels, respectively. (6) W: Weight due to the geographical distance between regions i and j. (7) *EK models* focus on a model with both individual and time-period fixed effects

5 Conclusion

Log likelihood

Hausman test

Number obs.

 σ^2

In this paper, we analyze convergence in relative income through technology transfer and absorption capacity among 11 Asian countries over the period 1970–2014. Following Barro and Sala-i-Martin (1997, 2004), and Novales et al. (2009), we present a model of Schumpeterian technology diffusion between two countries, one being a leader country in innovation, and the second being a follower that adopts the technology developed in the leader country. Through sensitivity analysis, we find that the results support both the absolute and conditional convergence hypothesis in Schumpeterian technology diffusion model.

We then extend the model to a multinational diffusion model to test the convergence hypothesis. Following Ertur and Koch (2007, 2011), Lesage and Pace (2009), and Elhorst (2010), we construct a dynamic spatial Durbin model (DSDM) for technology diffusion allowing spatial for interdependence. For an empirical test, we measure the technology shock (ratio of technology stocks of the follower country and the leader country) using the variable gap, which is measured by total factor productivity of the follower country relative to that of the leader country, the USA. We also assess the channels through which this shock of technology is transferred in combination with the absorption capacity of the following country, physical capital, human capital, and FDI.

DSDM is the most appropriate specification for the models based on the Schumpeterian technology diffusion results. The estimated coefficients on the lagged relative income are significant and negative at a level below 1%. These results support the convergence hypothesis among Asian countries. The total effect of human

0.001

1114.1 40.2 (0.00)***

540

capital investment rate, TFP, and trade on the growth of relative income is positive and significant. However, the coefficients and total effects of absorption capacity through physical and human capital vary from theoretical positive expected signs. One possible reason is that ratio of total factor productivity of the following country and leader country is decreasing. Otherwise, the investment ratios of Asian countries are too high which may be lead to the economies over-accumulated and then have a small negative effect on economic growth. The shock of technology is transferred by absorption capacity in combination with trade in Asian countries. Therefore, Asian countries should further promote trade liberalization, a channel for technology transfer, and markets.

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