International Area Studies Review
2026, Vol. 29(2) 159–182

https://doi.org/10.69473/iasr.2026.29.2.159

IASR

Article

The Effect of Knowledge Spillover on Productivity Enhancement in Asia Countries

Byung Min Soon
Professor, Department of Agricultural Economics, Chungnam National University, Daejeon, Republic of Korea

Hokyung Bang
Researcher, Center for International Development, Korea Development Institute, Sejong, Republic of Korea

Choongwon Lee*
Researcher, Korea Statistics Promotion Institute, Daejeon, Republic of Korea

Abstract

This research examines the impact of knowledge transfer on Total Factor Productivity (TFP) enhancement within APO (Asia Productivity Organization) member countries, focusing on the ICT (Information and Communications Technology) sector. It reveals that both domestic and foreign R&D capital stocks significantly boost productivity, with domestic inputs having a greater effect. The study underscores that larger technological gaps correlate with lower TFP, suggesting that narrowing these gaps through knowledge spillovers or improved human capital can increase productivity. Challenges are institutional barriers, limited absorptive capacity, and financial constraints hinder effective knowledge transfer. The findings advocate for targeted policies that enhance R&D investments, foster human capital development, and strengthen international R&D collaboration, particularly in developing nations, to optimize long-term productivity gains across various high-tech industries.

Keywords

Absorptive capacity, Asia, Fixed effect model, Human capital, ICT, Knowledge spillover, Productivity

Introduction

Knowledge spillover is crucial in elevating participation in Global Value Chains (GVCs) and serves as a wellspring of substantial added value. Piermartini and Rubínová (2014) underscored

Corresponding author:
* Email: cnddnjs0393@gmail.com

that knowledge exchange, often called knowledge spillovers, amplifies the intensity of interconnections within supply chains linking different countries. Furthermore, it has been recognized that knowledge spillovers traveling through these supply chains are more resilient than the conventional understanding, which relied on factors such as geographical proximity or the volume of trade flows. Singh (2004) notably reveals significant productivity improvements attributable to various sources. These include an industry's own research and development (R&D) efforts and the diffusion of knowledge from domestic and foreign sources. In essence, this research underscores the positive impact of knowledge spillovers on industry productivity, highlighting the importance of knowledge transfer in driving innovation and enhancing the competitiveness of industries within GVCs.

The stagnation in productivity growth is attributed to the slow accumulation of knowledge-based capital and the decrease of newly created enterprises. Labor productivity continued to rise from 1990 until the financial crisis but decreased. Both emerging and developing countries and OECD countries display similar labor productivity growth rates. Most countries are expected to experience a slowdown in potential global growth by 2060 due to a weakening labor force resulting from aging populations (Cho & Kim, 2021). Consequently, future economic growth will increasingly depend on advancements in TFP (McGowan et al., 2015). TFP is critical in investing in knowledge-based capital, implementing competition-friendly reform policies, and disseminating new technologies in advanced global companies. In the future, TFP's growth will significantly impact GDP growth more than labor or capital contributions. In particular, from the perspective of digital transformation, the productivity improvement of medium-high R&D, knowledge-intensive industries such as electrical equipment and machinery will be more important for growth. In general, these industries play an important role not only in reducing costs, but as a channel of interlinkage with other industries. Han (2018) estimated the returns of R&D investment and the magnitude of the spillover effect of all manufacturing companies. This study found that the social and private returns of domestic R&D investment relatively large in such as electric equipment, electronic parts, and computers calculated. In addition, the spillover effect of R&D in the electrical equipment and machinery industry was also relatively high among the entire manufacturing industry, excluding medical materials and pharmaceuticals.

Our study aims to estimate the effect of knowledge spillovers on productivity enhancement with special attention to knowledge-intensive industries (i.e., electrical equipment and machinery) thereafter referred to as the ICT industry. To achieve this, the procedures are set as below. First, a range of studies that explore the role, characteristics, and effects of knowledge spillovers on productivity growth are identified. Knowledge-based capital comprises intellectual property rights, management know-how, design, software, databases, etc. It is important in promoting technology dissemination and knowledge of advanced global companies. Second, a dynamic panel regression is used to analyze the empirical impact of knowledge spillovers on productivity. Finally, based on our empirical research findings, the study suggests policy implications focusing on the Asia Productivity Organization (APO) member countries. These implications may include promoting collaboration among firms and universities, investing in R&D, improving human capital through education and training, and enhancing institutional quality to facilitate knowledge diffusion and innovation, all of which can contribute to productivity growth. This methodology is adjudicated as appropriate, given its exposition of the causal nexus between knowledge transfer and productivity through the application of dynamic panel regression analysis.

Literature Review

The amalgamation of empirical research findings offers valuable insights into the intricate dynamics of knowledge transfer and spillovers in international trade and economic development. Knowledge spillovers occur not only domestically but also internationally. Generally, multinational enterprises from high-income countries would carry out much of the world's total R&D activities, possess the bulk of the world's stock of advanced commercial technologies and have most of the advanced technology. These advanced technologies are introduced to developing countries through multiple channels. However, no theoretical consensus has yet been reached on the international spillover path of knowledge (Fracasso & Vittucci Marzetti, 2015).

For empirical analysis, there is extensive literature on the impact of the R&D of other firms on the productivity of a particular firm in a closed economy. Despite differences in data, methodology, and measurement methods used in R&D, we found that R&D productivity ripple effects exist, although their significance varies significantly from study to study (Griliches, 1992).

Research on the international R&D spillover effect recently originates from Coe and Helpman (1995). They found that a country's TFP depended on accumulative domestic R&D capital and accumulative foreign R&D capital. Lichtenberg et al. (1998) has re-examined the results of Coe and Helpman's estimates, and the empirical results confirm that the more open to trade a country is, the more likely it is to benefit from foreign R&D. Coe and Helpman's method is continuously re-examined through improved econometric methods or different data sets, and each result has been made. Although unstable results are sometimes yielded, the main conclusions remain unchanged most of the time. Kao et al. (1999) methodologically studied the CH method with the panel cointegration method, and empirical results on TFP and domestic R&D capital stock have a positive relationship, yet trade-related international R&D spillover effects do not.

R&D capital stock is insufficiet to explain the innovative production process fully. This is the reason why other factors have been added to the Coe and Helpman (CH) model. Human capital variables are considered as direct factors of production (Engelbrecht, 1997, 2002; Fracasso & Marzetti (2015) as expected, prove to be statistically significant, while coefficient estimates of domestic R&D capital and international R&D spillover effects are found to be relatively small. Also, several institutional factor variables could be included to address the coefficient robustness issue. The productivity effects of international R&D spillovers largely depend on host country policy environments(Feinberg & Majumdar, 2001) and local enterprises' technical capabilities (Cantwell, 1993).

Supply chain linkages play a crucial role in shaping knowledge spillovers and productivity. Piermartini and Rubínová (2024) emphasize the significance of international supply chain connections in amplifying knowledge spillovers, showing their greater robustness compared to traditional determinants like geographical proximity. Active participation in supply chains is vital for economic development. Ubaldo et al. (2018) uses Irish firm-level data to explore intraindustry and intraregion spillovers through supply chain linkages, heterogeneity of investors, and domestic firms' absorptive capacity condition spillover effects from multinationals. Results reveal a negative link between foreign-owned firms' and domestic firms' productivity. Selling to foreign-owned firms has a positive effect, while buying from them negatively impacts domestic firms' average productivity. Kaur and Singh (2017) study the relationship between economic growth and knowledge economy variables in 19 developing countries. Positive impacts on TFP are observed with domestic knowledge stock, openness, and interaction terms of foreign R&D spillovers with openness, human capital, and FDI. Higher human capital and international trade lead to increased productivity growth through knowledge spillovers. Goncalves et al. (2021) assesses the role of trade openness as a technology transfer channel across 58 countries over 45 years. While trade openness variation temporarily boosts TFP, its level does not directly affect productivity growth. High- and middle-income countries experience positive effects, while low-income and emerging countries face negative impacts, especially when openness interacts with domestic knowledge stock.

Recent studies on R&D cooperation and innovation networks reveal diverse impacts on productivity and economic growth. Gömleksiz (2023) highlights the significant long-term growth contributions from high-tech imports and domestic knowledge, despite weak direct impacts from R&D cooperation itself, emphasizing the need for absorptive capacity. Bernal et al. (2022) explore various spillover scenarios in Spanish firms, indicating that knowledge spillovers can both enhance and restrict collaborative efforts, which in turn affect innovation performance. Eugster et al. (2018) and Chen and Dauchy (2018) underscore the importance of foreign knowledge and R&D in enhancing domestic innovation, particularly in technology-leading nations and competitive international environments. Studies by Min et al. (2020) and Kim et al. (2014) in the Republic of Korea (ROK) find that larger innovation networks and strong intellectual property rights significantly boost productivity, especially in high-tech and smaller firms. Crespi et al. (2020) identify positive productivity spillovers from certain public R&D investments in Chile, affected by firms' proximity and technological closeness. Singh (2004) notes the critical role of domestic and international knowledge spillovers in the ROK's manufacturing productivity, with shifts in significance across decades, suggesting evolving policy needs concerning technology and intellectual property rights.

Recent research underscores the critical role of intangible assets, especially human capital and absorptive capacity, in boosting productivity. Aghion and Jaravel (2015) stress the necessity of absorptive capacity for growth, while Demmou et al. (2019) link productivity growth to financial and institutional development. Nonnis et al. (2023) argue that the effectiveness of knowledge spillovers relies on the complementarities among domestic intangible assets, finding domestic spillovers more impactful than foreign ones. Audretshch et al. (2020) show that R&D and knowledge spillovers mutually enhance firm productivity, with R&D policies fostering broader investment and open innovation models increasing R&D demand. Ali et al. (2023) find that while knowledge spillovers boost total factor productivity, this benefit hinges on the quality of institutional frameworks, suggesting that strong policy complementarities are essential. Similarly, Jordaan et al. (2020) find that productivity spillovers in developing economies from multinational corporations depend on the interaction between corporate characteristics, local conditions, and the extent of local supplier utilization, emphasizing the importance of structural and institutional quality in maximizing these benefits.

Knowledge Spillover and Productivity Trends

Economic growth is one of the significant national goals worldwide and is always measured by the rate of indicator economic growth. Economic growth can be fostered by increasing the labor and capital inputs used in production. Figure 1 shows APO member countries' average GDP growth rate and growth rate decomposition. The economic growth rate of APO member countries has been above the global average since 1980. On average, it remained about 2% higher and decreased slightly before the COVID-19 crisis. The decline in growth due to the crisis was also affected less than the global average. The TFP in APO member countries was increasing its share of economic growth. Figure 1 can see that the growth contribution (gray box) by labor input is decreasing, while the productivity improvement (blue box) is increasing. It showed a sharp turnaround in the face of the COVID-19 crisis.

However, the economic growth rate and decomposition alone do not express the economy's productivity well. Productivity is widely accepted as a key economic performance indicator. Productivity is a concept related to increasing output through the same input, which is related to sustainable prosperity, economic efficiency, lower cost, and sustained competitiveness. The most widely used productivity indicator is labor productivity, such as output per worker, value-added units, or TFP.

Since the 1990s, the productivity growth rate of advanced countries has decreased, which is now at historically low levels (Adler et al., 2017). However, compared with developed countries, the productivity of APO member countries appears to be relatively higher, and before the COVID-19 crisis, it was around 2%. However, since the COVID-19 crisis, TFP has shown a rapid decline, and policy efforts to recover it are drawing attention.

Figure 2 shows the average TFP growth rate of APO member countries. For comparison, data from the APO productivity database, Penn World Table (PWT), and Conference Board were used, respectively. These three different data sets show the same trend but at different levels. It can be seen that the TFP growth rate of APO member states were growing steadily before 2012, except during the 1998 and 2008 crises. After the global financial crisis, APO member countries faced the problem of declining global productivity. In 2018, when it was recovering, TFP showed a sharp decline in the face of COVID-19 again.

It is known that economic growth and TFP have a close relationship and have a significant effect on the increase in income. TFP shows productivity changes according to measurable changes in factors, and representative factors include real capital stock, R&D investment (capital input side), quantitative input and human capital of labor (labor input side), learning effect, and technology transfer (market structure and openness side). The same pattern between economic

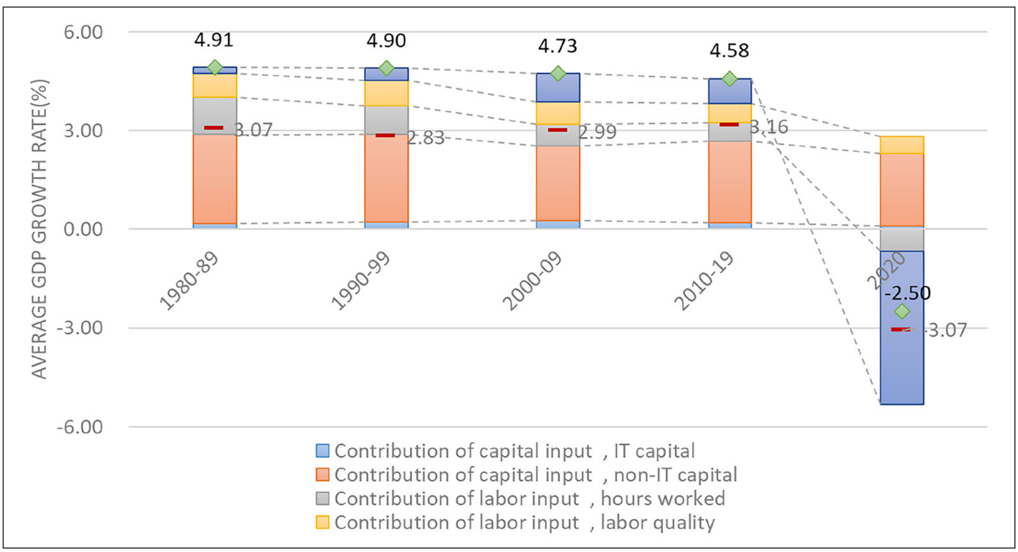

Figure 1. GDP Decomposition in APO countries,1980-2020

Source: APO Productivity Database 2022 Version 1, Updated 31 October 2022.

Note: APO member countries only, the value calculated as a simple average of the APO member countries and period due to the availability of the data. However, for 2020, single-year data are presented for comparison. World averages are shown in red lines, and the 1980s average was 3.07%. And APO averages are shown in green dots, and the 1980s average was 4.91%.

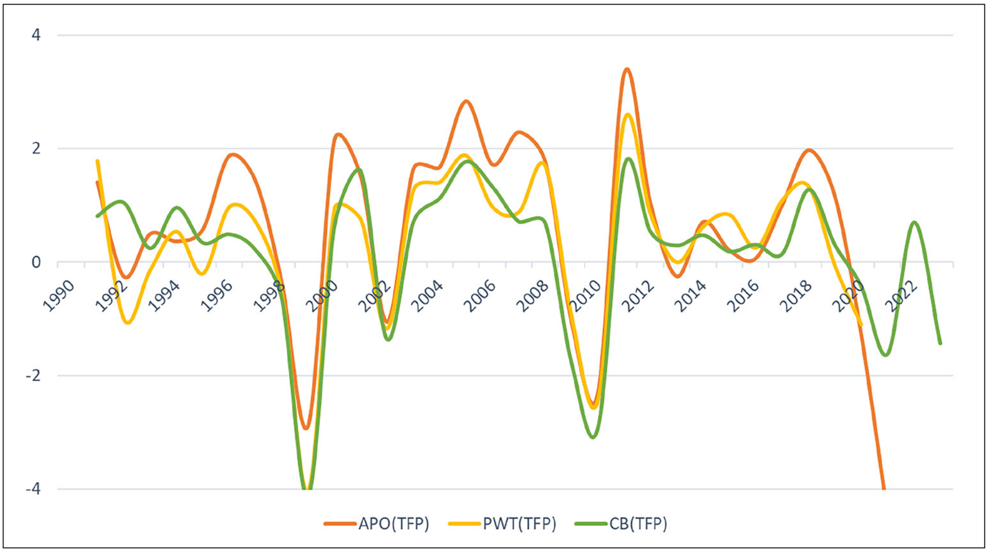

Figure 2. Comparison of Trend in TFP growth rate of APO countries, 1990-2022
Source: APO Productivity Database 2022 Version 1, Updated 31 October 2022.
PWT version 10.01, January 23, 2023.
The Conference Board Data, Growth Accounting and Total Factor, 2023. 05.03.
Note: APO member countries only, the value is calculated as a simple average of the APO member countries and period.

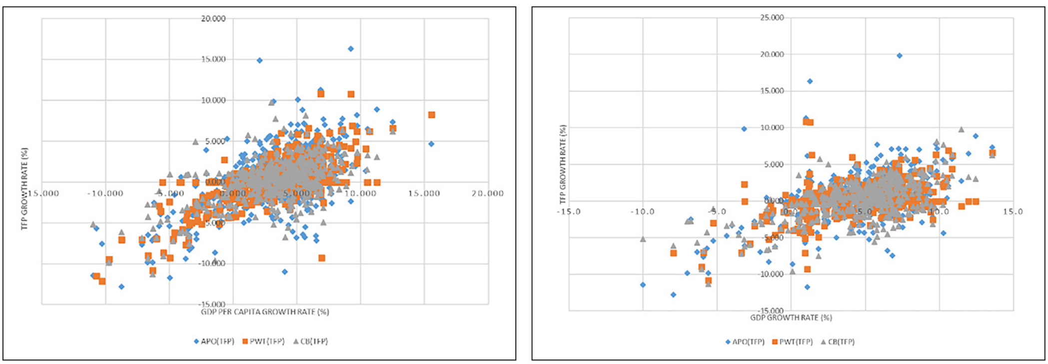

Figure 3. Relationship between GDP and TFP growth rate
Source: APO Productivity Database 2022 Version 1, Updated 31 October 2022.
Note: All APO member countries included, but outliers or the missing deleted, e.g., Bahrain's TFP (APO) does not exist.

growth and TFP can be seen in APO member countries, and the relationship between the economic growth rate and the TFP growth rate confirmed by available data has a strong positive relationship. Therefore, it proves that TFP can have a major impact on driving economic growth.

After the economic downturn, economic activity is reallocated from high-productivity sectors such as information and communication technology (ICT) to low-productivity sectors such as social services and real estate. This suggests that more productive sectors contract more during recessions (Aaronson et al., 2004). Therefore, this research estimates the impact of a high-productivity industry such as ICT on APO member country's productivity. In this research, due to the data availability, the ICT industry is defined as combining electrical machinery and apparatus, machinery and equipment n.e.c., office, accounting and computing machinery, radio, television, and communication equipment. In particular, it aims to estimate the effect of increasing productivity through knowledge spillover and review the barrier factors that hinder productivity improvement. Through this, productivity improvement in the ICT industry can create high value added during a period of economic recovery.

Analysis of Knowledge Spillover Effect

Method

In recent economic growth theories, trade is recognized as a crucial mechanism for disseminating knowledge across borders. Through international trade, domestic productivity experiences an upswing as products infused with foreign knowledge are imported. The quality of imported goods plays a pivotal role in this dynamic, intricately linked to foreign investments in R&D. Consequently, the augmentation of domestic productivity through trade is intimately connected to the influence of overseas R&D efforts.

A dynamic panel regression is employed to analyze the dynamic empirical impact of knowledge spillovers on productivity across various countries. To estimate dynamic effects in panel data, the model has current levels of productivity as a function of a proxy variable for knowledge transfer and other control variables. Our panel regression model includes a fixed-effect model specified as follows:

$$TFP_{i,t} = \alpha + \gamma K_{i,t} + \delta X_{i,t} + \theta_i + \mu_t + \epsilon_{i,t} \tag{1}$$

where the subscripts i and t represent country and periods, respectively. TFP is a total factor of productivity. K represents a knowledge variable. Thus, γ is the coefficient of primary interest, reflecting the productivity effect of knowledge transfer, and it is expected to be positive. X is a set of control variables that significantly impact productivity, such as domestic R&D stock, human capital, and other variables (trade openness, labor force, GDP growth, population, and inflation). These variables are in detail below. θ_i and μ_t are countries and time-fixed effects, respectively, and $\epsilon_{i,t}$ is the error term. The panel fixed effect controls the common characteristics between countries or the effect of common changes by year, it is generally evaluated as a useful method for analyzing the characteristics of individual countries.

Coe and Helpman (1995) pioneered domestic TFP based on endogenous growth theory. The study constructed a model influenced by overseas R&D capital stock. Additionally, the research considered the technological gap between countries. The basic model is outlined as follows, with the specified type.

$$TFP_{i,t} = \alpha + \gamma K_{i,t} + \delta X_{i,t} + \beta TG_{i,t} + \theta_i + \mu_t + \epsilon_{i,t} \tag{2}$$

where TG represents the technology gap. The technological gap of country i can be defined as the disparity between the total factor productivity of country i and other countries' average TFP. Hence, a positive technology gap for country i implies that it possesses a higher technology level than the average TFP of the reference APO target country. Accordingly, this technology gap can be used as a proxy for the TFP differential to gauge technological disparities across APO member economies.

Following Nelson and Phelps (1966) and Benhabib and Spiegel (1994), this was included to determine the impact of human capital as a determinant of long-term TFP. The study investigated how the impact of R&D on TFP changes by introducing human capital.

$$TFP_{i,t} = \alpha + \gamma K_{i,t} + \delta X_{i,t} + \beta TG_{i,t} + \mu HC_{i,t} + \theta_i + \mu_t + \epsilon_{i,t} \tag{3}$$

To assess the impact of Griffith et al. (2004) and Cameron et al. (2005) on technological innovation concerning the technological gap and absorptive capacity, a cross term involving human capital and the technological gap was introduced. The study aimed to investigate the role of human capital in augmenting TFP through technological innovation and to evaluate the effectiveness of improving absorptive capacity in enhancing domestic TFP by facilitating the introduction of technology.

$$TFP_{i,t} = \alpha + \gamma K_{i,t} + \delta X_{i,t} + \beta TG_{i,t} + \mu HC_{i,t} + \Omega TG_{i,t}{}^{*} HC_{i,t} + \theta_i + \mu_t + \epsilon_{i,t} \tag{4}$$

Apart from the contribution of human capital to boosting TFP through technological innovation, there is an opportunity to evaluate the impact of improving absorptive capacity. This involves enhancing the ability to absorb and implement technologies from leading countries, testing its effectiveness in elevating domestic TFP. In this context, let $TG^{*}HC$ denote the absorptive capacity of human capital, and Ω signify the specific effect or outcome resulting from this enhanced absorptive capacity. The goal is to assess how strengthening the capacity to adopt technologies from technologically advanced nations contributes to overall productivity growth.

Data

The dependent variables of this study are productivity-related variables such as GDP, value added, and TFP by industry. The "APO Productivity Databook" and "APO Productivity Database" contain data related to the macroeconomics and productivity of APO member countries, and this data is provided by the APO. This database covers data related to economic development from 1970 to 2020 from Asian countries, with economic growth projections and labor productivity improvement through 2030.

Alternatively, data from international organizations can be used. For example, it is possible to analyze using productivity data from the World Bank. In addition, it is possible to secure consistency through comparative analysis. Using macro data from APO member countries is also considered to calculate labor productivity for the sophisticated analysis through a specific classification of industries. To calculate productivity by sector, UNIDO's production, added value, and employment data by industry are used. Especially, to classify the ICT industry, Industry 29-32 based on ISIC were classified as ICT industries.

The explanatory variables of this study are the R&D expenditure variable provided by the OECD and UNIDO. However, if the missing value exists between the two periods, it is an imputation with the period average. Conversely, missing values existing at the beginning and end of the time-series were left in a missing state without imputation. Although it is not an elaborate interpolation method, it has been adjusted to increase data availability and suit the model. Then, the data expressed as the proportion of GDP was converted by multiplying the constant GDP as of 2015.

The R&D capital stock was obtained using the permanent inventory method, as in previous studies. The depreciation rate was assumed to be 5% and 15% as in CH, and the average growth rate (g) of R&D expenditure was calculated by averaging the logarithmic value of expenditures in 1996/2021 based on the data availability used in this study. However, the difference between 5% and 15% depreciation rates is not significant, so a 5% depreciation rate was applied in this study. According to Griliches (1980), the R&D capital stock for the initial year used in this study and the R&D capital stock by year using the permanent inventory method are as follows. *S* is R&D capital stock in the initial year, S_t^d is R&D capital stock by year by permanent inventory method, and RD is R&D investment amount. Subscripts *i* and *j* represent APO member countries, and *t* is the period, respectively.

$$S_{96}^d = \frac{RD_{96}}{0.05 + g}\ ,\ S_t^d = (1 - 0.05)S_{t-1}^d + RD_{t-1} \tag{5}$$

The foreign R&D capital stock flowing into the domestic economy obtains the total amount of technology embodied in imports by weighted average based on its income, and three overseas R&D capital stocks can be calculated according to the weight calculation method. Since trade measures the degree of interrelationships between different national economies, all foreign knowledge stocks should be weighted on average by imports from that country.

The weighted average is used in two ways, depending on CH and LP. First, according to the Coe and Helpman (1995) method, embodied knowledge from foreign countries uses import value between countries as weights, reflecting the direction of trade and deriving a long-term relationship between variables. The foreign knowledge stock flow is derived by a weighted average of imports from that country. In the following equation, S_{jt}^d is the R&D capital stock of country *j*, *M* used the trade amount data of the WITS, M_{ijt} is the import amount from country *j*, and M_{it} is the total import amount of country i.

$$S_{it}^{CH} = \sum_{j \neq i}(M_{ijt}/M_{it})S_{jt}^d \tag{6}$$

Lichtenberg and van Pottersberghe de la Potterie (1997) criticized the CH method, pointing out the possibility of aggregation bias and that it does not reflect the strength of trade. Accordingly, it was proposed to use the domestic import to the GDP of the other country as a weight for the overseas R&D capital stock instead of the total import. Finally, it can be obtained by simply averaging the R&D capital stock of each country.

This study measured knowledge transfer from abroad using a modified LP method to measure knowledge transfer between APO countries. This method was chosen due to the incomplete trade and R&D data between countries. In the following estimation, in the same way as the above equation *M* used the trade amount data of the WITS, and *Y* is the constant GDP as of 2015.

$$S_{it}^{LP} = \sum_{j \neq i}(M_{ijt}/Y_{jt})S_{jt}^d \tag{7}$$

Finally, the obstacles to accepting knowledge transfer in each country were considered. In addition, explanatory variables generally used to analyze productivity were included (Engelbrecht, 1997; Foster-Mcgregor et al., 2017). Therefore, the analysis included human capital, income level (GDP per capita), institution, regulation, foreign direct investment (FDI), and overseas development assistance (ODA).

Country-level data are used for 15 APO member countries observed between 1996 and 2020, collected primarily from OECD's Research and Development Statistics database, UNESCO's science, technology and innovation database, and the World Development Indicators' online database. Among the 21 APO member countries, Bangladesh, Cambodia, ROC, Nepal, Fiji, and Lao PDR were excluded due to data availability, as time-series gaps exist or some variables were missing in the target period. Detailed source, coverage, and descriptive statistics of the variables used in this study are as follows.

Results

Empirical Results on TFP

In Model (1), the study investigated how domestic and foreign research and development (R&D) capital stocks impact productivity. The results revealed a positive influence of only domestic R&D capital stocks on productivity. Importantly, the impact of foreign R&D capital stock is not significant. This indicates that when analyzing TFP from a capital input perspective, knowledge spillover from abroad does not have a substantial impact on domestic productivity.

Model (2) analyzed the impact of the technological gap and other factors on TFP. The results revealed a positive influence of both domestic and foreign R&D capital stocks on productivity. And it was found that the lower the technological gap in each country, the worse the TFP. This suggests that TFP will improve if one country can reduce its technological gap compared to other countries, and this can be achieved through knowledge spillover or domestic R&D capital input.

Following Nelson and Phelps (1966) and Benhabib and Spiegel (1994) this was included to determine the impact of human capital as a determinant of long-term TFP. In Model (3), an analysis included the human capital index to assess the role of human capital as a determinant of long-term TFP. The findings indicated that even when considering the human capital factor, overseas research, and development capital stock continues to exert an impact on productivity,

Table 1. Descriptive statistics of variables

Variable		Mean	St. Dev	Min	Max	N
Productivity	APO	0.9748	0.1014	0.6764	1.2281	375
	PWT	0.9337	0.1039	0.6150	1.1620	312
Tech gap		-0.0006	0.0841	-0.2710	0.3240	375
Knowledge	Domestic	7,056.11	7,492.24	4.10	32,017.30	339
	Foreign	3,006.51	3,769.40	1.30	22,245.30	339
Import Share	Total	0.1440	0.1453	0.0100	0.6300	353
	ICT	0.0615	0.0852	0.0000	0.4500	353
Other	Human capital	2.5890	0.5570	1.4690	4.3520	360
	Export	218,410.13	211,918.36	2,320.00	871,000.00	376
	Import	220,434.63	205,442.39	3,010.00	856,000.00	376
	Openness	1.0310	0.9928	0.1969	4.1224	376
	FDI inflow	14,390.22	24,891.72	-4,950.00	181,000.00	390
	ODA received	864.56	1,036.22	-939.00	4,220.00	291
	Role of law	0.1812	0.8198	-1.0537	1.8702	345
	Regulation	0.2107	0.9294	-1.7092	2.2553	345

Source: APO Productivity Data, PWT 10.01, The Conference Board Data Central, WB- Global Productivity, WITS etc.

Table 2. Major exporters and importers of charges for the use of intellectual property

Unit: Million USD, %

	Export Value in 2020	Export Value in 2021	Export Share in 10 economies_ 2020	Import Value in 2020	Import Value in 2021	Import Share in 10 economies_ 2020
European Union	144,002	163,303	37.5	206,018	242,204	50.5
Extra-EU exports	93,251	115,259	24.3	152,291	188,583	37.3
United States of America	115,558	124,613	30.1	47,708	43,342	11.7
Japan	43,065	47,860	11.2	37,629	46,889	9.2
United Kingdom	23,873	23,503	6.2	28,223	29,222	6.9
Switzerland	23,242	29,916	6.0	26,418	27,457	6.5
People's Republic of China	8,879	11,948	2.3	16,031	17,759	3.9
Singapore	8,673	11,648	2.3	15,345	17,813	3.8
Canada	7,210	8,535	1.9	13,684	16,311	3.4
ROK	6,855	8,023	1.8	9,890	11,130	2.4
United Arab Emirates	3,050	3,268	0.8	7,241	8,632	1.8

Source: WTO, World Trade Statistical Review 2022

and human capital also contributes positively to total factor productivity, although not significantly.

In Model (4), the study investigated the impact of the technology gap and absorptive capacity as defined by Griffith et al. (2004) and Cameron et al. (2005) on technological innovation. A cross term between human capital and the technological gap was introduced to assess its effect. The analysis aimed to test the role of human capital in enhancing TFP through technological innovation and to evaluate the effectiveness of improving absorptive capacity to boost domestic TFP by facilitating the introduction of technology from technologically advanced countries. The findings indicated that human capital contributes to increased TFP through technological innovation. In addition, it indicates that the reduction of technology gaps has a greater impact on TFP. Consequently, this implies that overall productivity can also rise by improving the country's technological gap by effectively utilizing human capital.

The findings of this study indicate that TFP is experiencing a positive impact due to the influence of research and domestic development capital stock in both developed and developing countries (Table 5). Meanwhile, foreign R&D capital stock appears to have a significant positive effect on total factor productivity in developing countries. This indicates that knowledge transfer from abroad in developing countries is a major factor in improving productivity. However, it was observed that the influence of the technological gap on TFP is more pronounced in developing countries than in developed ones. Additionally, while human capital growth in developing countries appears to have a positive effect on TFP, it was not a significant coefficient.

Empirical Results on ICT Productivity

Our study estimates the effect of productivity through knowledge spillover in the ICT industry. To do that, a variable for foreign ICT R&D stock is made. ICT productivity is calculated using UNIDO's Industrial Statistical Data, using ISIC industry classification that regards electrical machinery and apparatus, machinery and equipment n.e.c., office, accounting and computing

Table 3. The impact of knowledge transfer to TFP

	M1	M2	M3	M4
Domestic R&D stock	**0.0655****	**0.0649*****	**0.0595*****	**0.0579*****
	(2.45)	(6.49)	(5.84)	(5.26)
Foreign R&D stock	**0.0224**	**0.0184****	**0.0167****	**0.0169*****
	(1.01)	(2.56)	(2.69)	(3.11)
Technology gap		**-0.8206*****	**-0.8176*****	**-1.1842*****
		(-14.09)	(-16.39)	(-6.08)
Human capital			0.0305	**0.0355***
			(1.71)	(1.81)
Human capital *Technology gap				**0.1544***
				(1.92)
Constant	-0.8159***	-0.7771***	-0.7938***	-0.7936***
	(-4.90)	(-15.84)	(-22.04)	(-18.73)
Observations	307	307	307	307
R^2	0.559	0.856	0.859	0.861
Adjusted R^2	0.556	0.855	0.857	0.859

t statistics in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 4. Comparison of high- and middle-low-income groups

	High-income group		Middle-low income group	
	M2	M3	M2	M3
Domestic R&D stock	**0.088***	0.080	**0.055*****	**0.052*****
	(2.53)	(1.93)	(6.09)	(5.04)
Foreign R&D stock	0.007	0.008	**0.022*****	**0.019****
	(0.28)	(0.33)	(3.19)	(2.84)
Technology gap	**-0.765*****	**-0.725*****	**-0.826*****	**-0.835*****
	(-10.10)	(-8.41)	(-14.34)	(-14.99)
Human capital		0.022		0.034
		(0.72)		(0.76)
Constant	**-1.095*****	**-1.087*****	**-0.884*****	**-0.880*****
	(-6.17)	(-6.31)	(-12.51)	(-10.47)
Observations	93	93	214	214
R^2	0.886	0.888	0.848	0.850
Adjusted R^2	0.882	0.883	0.846	0.847

t statistics in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Note: High-income countries were classified according to the World Bank's national classification as of 2021. For other countries, middle-income and low-income were classified into one classification.

machinery, radio, television, and communication equipment as ICT industries. Labor productivity in the ICT industry is a concept that measures the number of workers as a denominator and the added value in molecules. Value added includes not only labor but also the value created by various factors of production. Meanwhile, the knowledge spillover effect of the ICT industry is measured by ICT import. The LP method described above was used in the same manner.

Table 5. The impact of knowledge transfer to productivity in the ICT industry

	M1	M2	M3	M4
Domestic R&D stock	**0.1980****	**0.1948****	0.1371	0.1271
	(2.47)	(2.53)	(1.67)	(1.59)
Foreign ICT R&D stock	**0.1755*****	**0.1756*****	**0.1607*****	**0.1617*****
	(4.37)	(3.96)	(3.00)	(3.32)
Technology gap		0.5485	0.5899	-0.7299
		(0.80)	(0.84)	(-0.22)
Human capital			0.2772	**0.3007***
			(1.72)	(1.86)
Human capital * Technology gap				0.5715
				(0.41)
Constant	1.4781**	1.5084**	1.432**	1.4603**
	(2.35)	(2.52)	(2.55)	(2.68)
Observations	297	297	290	290
R^2	0.567	0.574	0.583	0.585
Adjusted R^2	0.564	0.570	0.577	0.577

t statistics in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 6. Comparison of high- and middle-low-income groups

	High-income group		Middle-low-income group	
	M2	M3	M2	M3
Domestic R&D stock	0.2295	0.0418	**0.2112****	**0.2278****
	(2.06)	(0.42)	(2.30)	(2.56)
Foreign ICT R&D stock	0.0852	0.1288	**0.1764*****	**0.1875****
	(0.64)	(1.06)	(3.45)	(2.44)
Technology gap	-1.0618	-0.0575	0.8410	0.7805
	(-0.92)	(-0.06)	(1.22)	(1.14)
Human capital		**0.4730****		-0.1422
		(4.88)		(-0.29)
Constant	2.3521	2.6009**	1.1305	1.2403
	(2.30)	(3.34)	(1.67)	(1.38)
Observations	96	93	201	197
R^2	0.596	0.664	0.587	0.585
Adjusted R^2	0.583	0.649	0.581	0.576

t statistics in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Note: High-income countries were classified according to the World Bank's national classification as of 2021. For other countries, middle-income and low-income were classified into one classification.

In models (1) and (2), domestic R&D stock was found to have a positive effect on productivity, and no statistically significant coefficients were derived in the remaining models. However, in all models showed that foreign ICT R&D stock positively affected productivity. It was found that although a technological gap worsens productivity and an improvement of human capital strengthens productivity, it does not show consistent results. This suggests that even if ICT knowledge spillover is absorbed domestically, there is a limit to increasing productivity through technological innovation.

In advanced economies, productivity seems to be driven by human capital development. However, in developing countries, the impact on productivity is more pronounced with both foreign and domestic ITC R&D investments. Furthermore, the widening technology gap significantly hampers productivity in developing countries, and there is a notable lack of influence from human capital on productivity. Hence, it is crucial to thoroughly examine the factors hindering the transfer of human capital and knowledge to enhance productivity in the ICT industry and incorporate these insights into policymaking.

Policy Implication and Limitation

The enhancement of TFP can be achieved through the transfer of knowledge from one country to another. This phenomenon not only elevates the productivity levels within the recipient country but also positively impacts global productivity as the disseminated knowledge becomes integrated into various facets of production, such as capital and R&D, among others. This research investigates the potential of knowledge transfer in augmenting productivity across member countries of the APO. Additionally, a more detailed examination is conducted within the context of the ICT industries including the electronics and electrical industries.

The study highlights a positive correlation between domestic and foreign R&D capital stocks and productivity. Notably, the impact of domestic R&D capital stock was more substantial than that of its foreign counterpart, but, underscoring the significant influence of knowledge spillover from foreign sources also on domestic productivity. Moreover, the research identified that a wider technological gap in each country correlates with lower TFP. This suggests that enhancing TFP is attainable by narrowing the technological gap relative to other countries, a feat achievable through knowledge spillover or the cultivation of human capital. The results also demonstrated that human capital contributes to increased TFP through technological innovation, emphasizing the potential for overall productivity improvement by effectively leveraging human capital to bridge the country's technological gap.

The study reveals a favorable effect stemming from the influence of R&D capital stock in developed and developing countries. Notably, the impact of the technological gap on TFP is more accentuated in developing countries than in developed ones in APO member countries. Furthermore, an increase in human capital in developing nations appears to have a positive correlation with TFP, suggesting that improving human capital could enhance overall productivity by narrowing the technology gap.

Our study focuses on estimating the impact of knowledge spillover on productivity within the ICT industry. The analysis indicates a positive correlation between domestic R&D stock and productivity. Moreover, the findings reveal statistically consistent and significant positive effect of foreign ICT R&D stock on productivity. Despite the aggravation of productivity due to a widening technological gap, introducing human capital does not seem to generate absorptive capacity. This implies that while the domestic absorption of ICT knowledge occurs, there are constraints on leveraging technological innovation to enhance productivity further.

The analysis results of classifying the country's income level showed that it is important to reduce the technology gap and increase openness (Appendix table A1). These results are consistent with previous studies. In developed countries, factors such as the development of human resources, the establishment of research networks, the strengthening of corporate-level technology absorption capacity, international R&D cooperation, and domestic intellectual property protection appear to be more important than the capital accumulation or capital input. In addition, since the major policy tasks facing each country are different, it appears that research by country is being conducted to solve them. And beyond the knowledge spillover, research on the reverse knowledge spillover is also being conducted.

Therefore, from the perspective of policymakers, policies to increase the inflow of R&D capital stock and national-level R&D investment policies are expected to be effective in developing countries, and policies to improve the quality of domestic human capital and establish an international R&D cooperation system are expected to be effective in developed countries. And basically, from a long-term perspective, it believes that human resource development policies should be accompanied.

Knowledge spillover in APO member countries can be impeded by various factors, with notable obstacles including institutional barriers, limited absorptive capacity, and financial constraints. Institutional barriers, exemplified by inadequate protection of intellectual property rights in certain nations, hinder foreign technology inflow due to unmet appropriability conditions. The absence of skilled human resources poses a challenge in absorbing and internalizing knowledge transmitted from abroad. Developing a competent workforce and enhancing vocational skills demand substantial national-level efforts and investment, including forecasting labor demand and formulating suitable education programs. In case of financial barriers, if domestic funding is inherently insufficient or the financial system is not well developed, posing challenges in mobilizing external funds, the realization of knowledge spillover benefits may be difficult. It is particularly so for intangible assets that face more difficulty securing loans. Policies to develop capital markets technology guarantee and rating systems are required in many countries. Additionally, even with FDI inflow, the transferred knowledge may be confined within MNCs and not easily disseminated to other firms and industries. Overcoming this limitation necessitates government intervention, encompassing incentives for MNCs, technological licensing, strategic partnerships, and substantial investments in national science, technology, and research and development (S&T and R&D) to maximize the international knowledge spillover effect.

The process of knowledge spillover from abroad to impact domestic productivity may involve a significant time lag. Acquiring new or essential knowledge is one step, but its utilization within the relevant industry takes additional time. To address this delay, policies are crucial to expedite the application of overseas patents and promote swift utilization of foreign knowledge by domestic companies. Government interventions, such as the removal of obstacles hindering the application of foreign patents, along with the provision of active tax benefits, can facilitate the rapid assimilation and application of overseas knowledge within the domestic industry.

Moreover, when MNCs establish a presence in a specific country, they often refrain from subcontracting to local firms and typically utilize inexpensive local labor solely for assembling imported components into finished products. While this may yield short-term advantages, it does not facilitate knowledge spillover. Local entities do not reap the benefits of acquiring advanced skills, sophisticated management practices, improved technologies, and training opportunities. In the cases of ROK and ROC, various regulatory measures were implemented to attract multinational companies and encourage technology transfer, resulting in the emergence of world-class multinational corporations. To enable APO member countries to effectively absorb knowledge transfer from multinational companies within their borders, the role of government regulations that enhance human capital and absorptive capacity becomes paramount.

In conclusion, the research underscores the critical role of knowledge spillover, particularly in the medium high R&D and knowledge-intensive industries (i.e., electrical equipment and machinery sector), for enhancing TFP across APO member countries. The positive correlation between domestic and foreign R&D capital stocks and productivity highlights the substantial impact of knowledge spillovers from foreign sources. However, challenges such as institutional barriers, limited absorptive capacity, and financial constraints can impede effective knowledge spillover. Policymakers should focus on reducing the technological gap, increasing openness, and implementing policies tailored to the specific needs of both advanced and emerging APO member countries. Additionally, fostering human capital development and establishing international R&D cooperation systems are crucial for long-term productivity improvements. Overcoming obstacles to knowledge spillover requires strategic government interventions, including incentives for MNCs, technological licensing, and investments in science, technology, research, and development.

Acknowledgment

This manuscript is based in part on a previously published international report, APO Productivity Outlook 2024 (Asian Productivity Organization, 2024). The present article substantially revises and expands that work, and the relevant portions are used here with appropriate permission and acknowledgment.

AI Acknowledgment

Generative AI or AI-assisted technologies were not used in any way to prepare, write, or complete essential authoring tasks in this manuscript.

Conflict of Interest

The authors declare that there are no conflicts of interest in this research.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

References

Aaronson, D., Rissman, E. R., & Sullivan, D. G. (2004). Can sectoral reallocation explain the jobless recovery? *Economic Perspectives-Federal Reserve Bank of Chicago*, *28*(2), 36–49.

Adler, G., Duval, R., Furceri, D., Çelik, S. K., Koloskova, K., & Ribeiro, M. P. (2017). *Gone with the headwinds: Global productivity*. IMF Staff Discussion Notes No. 2017/004.

Aghion, P., & Jaravel, X. (2015). Knowledge spillovers, innovation and growth. *The Economic Journal*, *125*(583), 533–573.

Ali, N., Hayat, U., & Manan, S. (2023). Knowledge spillover and domestic productivity across countries: The role of economic opportunities. *International Journal of Contemporary Issues in Social Sciences*, *2*(4), 1428–1445.

Audretsch, D., & Belitski, M. (2020). The role of R&D and knowledge spillovers in innovation and productivity. *European Economic Review*, *123*(C).

Benhabib, J., & Spiegel, M. (1994). The role of human capital in economic development evidence from aggregate cross-country data. *Journal of Monetary Economics*, *34*(2), 143–173.

Bernal, P., Carree, M., & Lokshin, B. (2022). Knowledge spillovers, R&D partnerships and innovation performance. *Technovation*, *115*.

Cameron, G., Proudman, J., & Redding, S. (2005). Technological convergence, R&D, trade and productivity growth. *European Economic Review*, *49*(3), 775–807.

Cantwell, J. A. (1993). Corporate technological specialisation in international industries. In *Industrial concentration and economic inequality* (pp. 216–232).

Chen, S., & Dauchy, E. (2018). *International technology sourcing and knowledge spillovers: Evidence from OECD countries*. International Monetary Fund.

Cho, S., & Kim, J. R. (2021). Population aging in Korea: implications for fiscal sustainability. *Seoul Journal of*

Economics, *34*(2), 238–264.
Coe, D. T., & Helpman, E. (1995). International R&D spillovers. *European Economic Review, 39*(5), 859–887.
Crespi, G., Garone L. F., Maffioli, A., & Stein, E. (2020). Public support to R&D, productivity, and spillover effects: Firm-level evidence from Chile. *World Development*, *130*(4).
Demmou, L., Stefanescu, I., & Arquie, A. (2019). *Productivity growth and finance: The role of intangible assets-A sector level analysis*. Economics department working papers No. 1547.
Engelbrecht, H. (1997). International R&D spillovers, human capital and productivity in OECD economies: An empirical investigation. *European Economic Review*, *41*(8), 1479–1488.
Engelbrecht, H. (2002). Human capital and international knowledge spillovers in TFP growth of a sample of developing countries: An exploration of alternative approaches. *Applied Economics*, *34*(7), 831–841.
Engelbrecht, H. J. (1997). International R&D spillovers, human capital and productivity in OECD economies: An empirical investigation. *European Economic Review*, *41*(8), 1479–1488.
Eugster, J., Ho, G., Jaumotte, F., & Piazza, R. (2018). *International knowledge spillovers*. IMF Working Paper No. 18/269. https://ssrn.com/abstract=3333721
Feinberg, E., & Majumdar, K. (2001). Technology spillovers from foreign direct investment in the Indian pharmaceutical industry. *Journal of international Business Studies*, *32*(3), 421–437.
Foster-McGregor, N., Pöschl, J., & Stehrer, R. (2017). The importance of absorptive capacities: Productivity effects of international R&D spillovers through intermediate inputs. *Economics of Innovation and New Technology*, *26*(8), 719–733.
Fracasso, A., & Vittucci Marzetti, G. (2015). International trade and R&D spillovers. *Journal of International Economics*, *96*(1), 138–149.
Gömleksiz, M. (2023). International knowledge spillovers and economic growth: New evidence from high-tech imports and R&D cooperation. *Istanbul Journal of Economics*, *73*(1), 281–306.
Gonçalves, E., Taveira, G., Labrador, A., & Pio, J. G. (2021). Is trade openness a carrier of knowledge spillovers for developed and developing countries? *Structural Change and Economic Dynamics*, *58*(C), 66–75.
Griffith, R., Redding, S., & Van Reenen, J. (2004). Mapping the two faces of R&D: Productivity growth in a panel of OECD industries. *Review of Economics and Statistics*, *86*(4), 883–895.
Griliches, Z. (1980). R & D and the productivity slowdown. *The American Economic Review*, *70*(2), 343–348.
Griliches, Z. (1992). The search for R&D spillovers. *Scandinavian Journal of Economics*, *94*, 29–47.
Han, J. (2018). *Measuring social returns to R&D and two countervailing spillovers*. KDI Policy Study 2018-18(Kor). https://ssrn.com/abstract=3491580
Jordaan, J., Douw, W., & Qiang, C. Z. (2020). *Multinational corporation affiliates, backward linkages, and productivity spillovers in developing and emerging economies: Evidence and policy making* (Policy Research Working Paper Series 9364). The World Bank.
Kao, C., Chiang, M., & Chen, B. (1999). International R&D spillovers: An application of estimation and inference in panel cointegration. *Oxford Bulletin of Economics and Statistics*, *61*, 691–709.
Kaur, M., & Singh, L. (2017). Knowledge spillovers across developing. *Seoul Journal of Economics*, *30*(3), 319–352.
Kim, T., Maskus, K., & Oh, K. Y. (2014). Effects of knowledge spillovers on knowledge production and productivity growth in Korean manufacturing firms. *Asian Economic Journal*, *28*(1), 63–79.
Lichtenberg, F. R., & van Pottelsberghe de la Potterie, B. (1998). International R&D spillovers: A comment. *European Economic Review*, *42*(8), 1483-1491.
McGowan, M. A., Andrews, D., Criscuolo, C., & Nicoletti, G. (2015). *The future of productivity*. OECD.
Min, S., Kim, J., & Sawng, Y. W. (2020). The effect of innovation network size and public R&D investment on regional innovation efficiency. *Technological Forecasting and Social Change*, *155*.
Nelson, R. R., & Phelps, E. S. (1966). Investment in humans, technological diffusion, and economic growth. *The American Economic Review*, *56*(1/2), 69–75.
Nonnis, A., Bounfour, A., & Kim, K. (2023). Knowledge spillovers and intangible complementarities: Empirical case of European countries. *Research Policy*, *52*(1).
Piermartini, R., & Rubínová, S. (2014). *Knowledge spillovers through international supply chains* (WTO working paper ERSD-2014-11). World Trade Organization.

Singh, L. (2004). Technological progress, structural change and productivity growth in the manufacturing sector of South Korea. *World Review of Science, Technology and Sustainable Development*, *1*(1), 37–49.

Ubaldo, M., Lawless, M., & Siedschlag, I. (2018). *Productivity spillovers from multinational activity to local firms in Ireland*. OECD Productivity Working Papers No. 16.

Appendix

Model Robustness Check

The following table shows the analysis results, including other control variables, to verify the robustness of the data used in the analysis and the model. In addition to the basic model, FDI inflow, income level, and rule of law variables were added to examine the main variables' coefficient changes. As a result of the analysis, it was found that the coefficient of the extra control variables was not significant, and reduced data availability caused distorted estimation results.

Table A1. The impact of knowledge spillover to TFP (APO)

	M1	M2	M3	M4	M5	M6	M7	M8
Domestic R&D stock	**0.065****	**0.065*****	**0.059*****	**0.058*****	**0.059*****	**0.063*****	**0.057*****	**0.075*****
	(2.45)	**(6.49)**	**(5.84)**	**(5.26)**	**(6.11)**	**(6.91)**	**(6.80)**	**(6.89)**
Foreign R&D stock	0.022	**0.018****	**0.017****	**0.017*****	**0.011****	**0.011***	0.003	-0.002
	(1.01)	**(2.56)**	**(2.69)**	**(3.11)**	**(2.46)**	**(2.14)**	(0.45)	(-0.22)
Technology gap		**-0.821*****	**-0.818*****	**-1.184*****	**-1.360*****	**-1.381*****	**-1.454*****	**-1.618*****
		(-14.09)	**(-16.39)**	**(-6.08)**	**(-8.03)**	**(-7.42)**	**(-7.78)**	**(-6.08)**
Human capital			0.030	**0.035***	0.023	0.019	0.017	0.013
			(1.71)	**(1.81)**	(1.47)	(1.22)	(1.06)	(1.23)
TG * HC				**0.154***	**0.244*****	**0.254*****	**0.294*****	**0.389*****
				(1.92)	**(3.51)**	**(3.50)**	**(4.27)**	**(3.33)**
Openness					**0.056*****	**0.057*****	**0.058*****	**0.076*****
					(4.39)	**(4.61)**	**(5.52)**	**(6.43)**
FDI inflow						-0.001	-0.002	0.000
						(-0.46)	(-0.99)	(0.07)
GDP per capita							0.056	
							(1.71)	
Rule of law								-0.001
								(-0.21)
Constant	-0.816***	-0.777***	-0.794***	-0.794***	-0.803***	-0.799***	-1.142***	-0.947***
	(-4.90)	(-15.84)	(-22.04)	(-18.73)	(-20.03)	(-12.10)	(-4.78)	(-8.43)
Observations	307	307	307	307	297	290	290	137
R^2	0.559	0.856	0.859	0.861	0.849	0.854	0.857	0.881
Adjusted R^2	0.556	0.855	0.857	0.859	0.846	0.851	0.853	0.874
sigma_u	0.177	0.171	0.163	0.160	0.169	0.174	0.209	0.163
sigma_e	0.057	0.033	0.032	0.032	0.031	0.031	0.031	0.028
rho	0.906	0.965	0.962	0.961	0.967	0.969	0.979	0.971

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

The analysis results divided by the country's average income level were additionally presented. In high-income countries, it was confirmed that the technology gap and openness had a significant influence. On the other hand, in middle-low-income countries, both foreign and domestic R&D capital stock are confirmed to be significant variables, and openness also affects productivity improvement.

Table A2. The impact of knowledge spillover to TFP (APO): High income

	M2	M3	M4	M5	M6
Domestic R&D stock	**0.088****	0.080	0.080	0.046	**0.074****
	(2.53)	(1.93)	(1.93)	(1.41)	**(3.22)**
Foreign R&D stock	0.007	0.008	0.000	0.005	-0.006
	(0.28)	(0.33)	(0.02)	(0.31)	(-0.41)
Technology gap	**-0.765*****	**-0.725*****	-3.304	**-1.127***	**-1.165***
	(-10.10)	**(-8.41)**	(-2.09)	**(-2.44)**	**(-2.36)**
Human capital		0.022	0.015	0.042	0.026
		(0.72)	(0.70)	(2.02)	(1.82)
TG * HC			0.834	0.229	0.229
			(1.70)	(1.78)	(1.61)
Openness				**0.097****	**0.075****
				(3.57)	**(4.68)**
FDI inflow					-0.000
					(-0.05)
Constant	-1.095***	-1.087***	-0.987**	-0.915***	-1.037**
	(-6.17)	(-6.31)	(-4.48)	(-6.44)	(-5.05)
Observations	93	93	93	93	90
R^2	0.886	0.888	0.895	0.919	0.929
Adjusted R^2	0.882	0.883	0.889	0.913	0.923
sigma_u	0.173	0.161	0.161	0.076	0.037
sigma_e	0.030	0.029	0.029	0.025	0.024
rho	0.972	0.968	0.969	0.900	0.698

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table A3. The impact of knowledge spillover to TFP (APO): Middle-low income

	M2	M3	M4	M5	M6
Domestic R&D stock	**0.055*****	**0.052*****	**0.052*****	**0.058*****	**0.074****
	(6.09)	**(5.04)**	**(4.85)**	**(3.99)**	**(3.22)**
Foreign R&D stock	**0.022*****	**0.019****	**0.019*****	0.015	-0.006
	(3.19)	**(2.84)**	**(3.22)**	(1.79)	(-0.41)
Technology gap	**-0.826*****	**-0.835*****	**-1.082*****	**-1.079*****	**-1.165***
	(-14.34)	**(-14.99)**	**(-5.29)**	**(-4.85)**	**(-2.36)**
Human capital		0.034	0.036	0.025	0.026
		(0.76)	(0.73)	(0.54)	(1.82)
TG * HC			0.110	0.104	0.229
			(1.23)	(0.89)	(1.61)
Openness				0.035	**0.075****
				(1.01)	**(4.68)**
FDI inflow					-0.000
					(-0.05)
Constant	-0.652***	-0.685***	-0.686***	-0.728***	-1.037**
	(-15.55)	(-17.01)	(-13.64)	(-16.07)	(-5.05)
Observations	214	214	214	204	90
R^2	0.848	0.850	0.850	0.813	0.929
Adjusted R^2	0.846	0.847	0.847	0.807	0.923
sigma_u	0.126	0.111	0.110	0.118	0.037
sigma_e	0.033	0.033	0.033	0.033	0.024
rho	0.934	0.918	0.916	0.927	0.698

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

The same robustness check was performed for ICT labor productivity and ICT R&D capital stock. In the case of the ICT industry, the effect of foreign R&D stocks was more pronounced, and the impact of human capital was consistently positive. As in the above results, the extra control variables' coefficient was insignificant, and reduced data availability caused distorted estimation results.

Table A4. The impact of ICT knowledge spillover on ICT productivity

	M1	M2	M3	M4	M5	M6	M7	M8
Domestic R&D stock	**0.198****	**0.195****	0.137	0.127	0.118	0.128	0.069	0.109
	(2.47)	**(2.53)**	(1.67)	(1.59)	(1.46)	(1.61)	(0.98)	(0.99)
Foreign ICT R&D stock	**0.176*****	**0.176*****	**0.161*****	**0.162*****	**0.177*****	**0.143****	0.099	0.171*
	(4.37)	**(3.96)**	**(3.00)**	**(3.32)**	**(3.18)**	**(2.36)**	(1.64)	(1.83)
Technology gap		0.549	0.590	-0.730	-0.709	-1.526	-1.853	0.512
		(0.80)	(0.84)	(-0.22)	(-0.19)	(-0.40)	(-0.55)	(0.43)
Human capital			0.277	**0.301***	**0.331****	**0.328****	**0.305***	**0.336*****
			(1.72)	**(1.86)**	**(2.25)**	**(2.30)**	**(2.06)**	**(5.08)**
TG * HC				0.572	0.550	0.869	1.060	-0.491
				(0.41)	(0.34)	(0.52)	(0.72)	(-0.98)
Openness					-0.139	-0.117	-0.108	-0.118
					(-0.73)	(-0.60)	(-0.61)	(-0.58)
FDI inflow						0.029	0.022	-0.014
						(0.90)	(0.68)	(-0.59)
GDP per capita							0.389	
							(1.13)	
Rule of law								-0.015
								(-0.25)
Constant	1.478**	1.508**	1.432**	1.460**	1.512**	0.997	-1.360	2.165***
	(2.35)	(2.52)	(2.55)	(2.68)	(2.77)	(1.27)	(-0.60)	(3.70)
Observations	297	297	290	290	289	282	282	132
R^2	0.567	0.574	0.583	0.585	0.594	0.593	0.600	0.633
Adjusted R^2	0.564	0.570	0.577	0.577	0.586	0.583	0.589	0.609
sigma_u	0.476	0.478	0.437	0.437	0.503	0.483	0.299	0.652
sigma_e	0.237	0.235	0.231	0.231	0.225	0.222	0.220	0.190
rho	0.802	0.805	0.781	0.782	0.833	0.825	0.648	0.922

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

The ICT industry was also analyzed by dividing the national income level. In high-income countries, most variables except human capital were not found to be significant. In other words, ICT productivity in high-income countries could be confirmed through more sophisticated corporate-level analysis. On the other hand, in middle-low-income countries, both foreign and domestic R&D capital stock are confirmed to be significant variables as in the above results. Especially, in Model 5, the intersection term shows a significant positive effect, which means that if there is no technology gap, the productivity improvement effect through human capital is great.

Table A5. The impact of ICT knowledge spillover to ICT productivity: High-income

	M2	M3	M4	M5	M6
Domestic R&D stock	0.229	0.042	0.049	0.124	0.234
	(2.06)	(0.42)	(0.50)	(0.60)	(1.36)
Foreign ICT R&D stock	0.085	0.129	0.151	0.140	0.112
	(0.64)	(1.06)	(1.21)	(0.99)	(0.76)
Technology gap	-1.062	-0.058	9.394	4.611	5.432
	(-0.92)	(-0.06)	(0.76)	(0.32)	(0.46)
Human capital		**0.473****	**0.500****	0.441	0.368
		(4.88)	**(3.39)**	(2.32)	(2.31)
TG * HC			-3.049	-1.723	-2.091
			(-0.82)	(-0.42)	(-0.63)
Openness				-0.215	-0.317
				(-0.54)	(-0.88)
FDI inflow					-0.008
					(-0.30)
Constant	2.352	2.601**	2.217	2.055	1.666
	(2.30)	(3.34)	(2.22)	(2.03)	(2.02)
Observations	96	93	93	93	90
R^2	0.596	0.664	0.672	0.680	0.700
Adjusted R^2	0.583	0.649	0.653	0.658	0.674
sigma_u	0.519	0.425	0.416	0.673	1.019
sigma_e	0.204	0.186	0.185	0.184	0.182
rho	0.866	0.839	0.834	0.931	0.969

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table A6. The impact of ICT knowledge spillover to ICT productivity: Middle-low income

	M2	M3	M4	M5	M6
Domestic R&D stock	**0.211****	**0.228****	**0.187****	**0.226****	0.234
	(2.30)	**(2.56)**	**(2.23)**	**(3.02)**	(1.36)
Foreign ICT R&D stock	**0.176*****	**0.188****	**0.191*****	**0.137***	0.112
	(3.45)	**(2.44)**	**(3.46)**	**(2.07)**	(0.76)
Technology gap	0.841	0.780	-5.490	**-8.610***	5.432
	(1.22)	(1.14)	(-1.33)	**(-1.89)**	(0.46)
Human capital		-0.142	-0.081	-0.162	0.368
		(-0.29)	(-0.23)	(-0.53)	(2.31)
TG * HC			2.927	**4.502***	-2.091
			(1.49)	**(2.03)**	(-0.63)
Openness				0.341	-0.317
				(1.42)	(-0.88)
FDI inflow					-0.008
					(-0.30)
Constant	1.131	1.240	1.437*	1.401*	1.666
	(1.67)	(1.38)	(1.98)	(2.15)	(2.02)
Observations	201	197	197	196	90
R^2	0.587	0.585	0.611	0.643	0.700
Adjusted R^2	0.581	0.576	0.600	0.632	0.674
sigma_u	0.372	0.416	0.372	0.405	1.019
sigma_e	0.244	0.243	0.236	0.222	0.182
rho	0.698	0.746	0.712	0.769	0.969

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$