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RESEARCH ARTICLE

International Knowledge Spillovers and Economic Growth: New Evidence from High-Tech Imports and R&D Cooperation*

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ABSTRACT
The diffusion of knowledge is an essential triggering factor in the phase of economic growth through externalities mostly based on R&D and innovations embodied in technological products or services. As a form of transmission, knowledge spillovers arising from an external source can emerge through various channels. This study investigates the effect of knowledge spillovers via high-tech imports and international R&D cooperation on long-run economic growth, in a panel of selected emerging and developing economies for the 1995-2019 period. Based on the results of second-generation econometric methods that take into account cross-section dependence and parameter heterogeneity, it is concluded that knowledge spillovers via high-tech imports are a prominent determinant of economic growth. The results also confirm the growth-enhancing effect of domestic knowledge stock as a measure of knowledge absorption capacity. However, it is deduced that knowledge spillovers via R&D cooperation have a weak and somewhat insignificant positive impact on economic growth, when ignoring the complementary relationship between incoming knowledge and the absorptive capacity of countries. Accordingly, the results indicate the essential role of increasing absorptive capacity in gains from R&D spillovers. Lastly, human capital seems to be decisive in the growth process.

Keywords: Knowledge spillovers, High-tech imports, R&D cooperation, Economic growth
JEL Classification: C33, D62, O33

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1. Introduction

In the past two decades, the main interest in the sources of economic growth has been considerably shifted to knowledge creation and technological advances arising from global production chains. Accordingly, it has been observed that the economic performance of countries heavily depends on the ability to use, accumulate, and develop knowledge in the new economic order (Narula, 2004). Apart from the recent increases in knowledge capital investments, particularly in developed economies, various channels that provide the share of knowledge through formal and informal ways also play an important role in the sustainability of growth (Organisation for Economic Co-operation and Development [OECD], 1996, 2013).

As a form of transmission, knowledge spillovers generally define the diffusion of knowledge arising from research and development (R&D) activities that are unable to be claimed as intellectual property (Kaiser, 2002). Van Stel (2006) states that knowledge spillovers occur when taking advantage of a technological innovation or product improvement that is introduced without any compensation. Hence, spillovers refer to knowledge not available elsewhere, thereby creating value for other economic agents. While the beneficiaries of spillovers can use external knowledge to assimilate or imitate existing technologies, developing new products or processes is also considered as input in R&D activities (Fischer, 2006). In the growth literature, the center of attention regarding knowledge spillovers is associated with positive externalities, which have some important advantages for knowledge recipients, especially in emerging and developing economies (Karlsson, Flensburg, & Hörte, 2004). Such externalities are realized in a range of interconnected processes. Accordingly, R&D activities that create new technologies are fed from a former stock of (external) knowledge that is assumed to be accessible at no cost, along with internal resources. Inventions and innovations based on R&D provide a high value added to the owner, as well as increasing the domestic knowledge stock. As the stock of knowledge grows over time, it allows more innovation to emerge without causing any increase in input costs. Hence, knowledge spillovers act as the engines of endogenous growth without being subject to diminishing returns (Branstetter, 1998; Basile, Capello, & Caragliu, 2011). Moreover, knowledge spillovers can contribute significantly to productivity and growth through economies of scale and the disclosure of tacit knowledge necessary to sustain learning with a range of interactions (Görg & Greenaway, 2004).

The literature on knowledge diffusion points to different channels of spillovers. In this sense, some part of the knowledge may be specific to a spatial unit (firm, industry, region, etc.) at a national level (Griliches, 1979, 1992; Scherer, 1984), while the rest is transmitted by sources from abroad (Grossman & Helpman, 1990; Coe & Helpman, 1995). Based on the fact that economic agents cannot unconditionally succeed with internal sources, the level of domestic knowledge and technology also enables the efficient transmission of external knowledge as a form of absorptive capacity (Jaffe, 1986; Cohen & Levinthal, 1989; Lane, Salk, & Lyles, 2001). Similarly, the technology gap and lack of human capital emerging at different scales have a potential impact on the benefit from knowledge spillovers arising from high-tech firms, sectors, or countries (Gorodnichenko, Svejnar, & Terrell, 2007).

This study aims to investigate the effect of knowledge spillovers via high-tech imports and international R&D cooperation on economic growth, in a panel of selected emerging and developing economies for the 1995-2019 period. As part of the growth process, the study also examines the relationship between knowledge absorption capacity defined by the domestic knowledge stock and collaborative R&D spillovers. The originality of the study is said to be two-fold. First, as far as is known, a significant body of research deals with knowledge spillovers on the axis of productivity differences, while others focus on inter-industry growth dynamics. In this respect, the study provides a cross-country contribution to the growth literature. Secondly, the study conducts second-generation econometric methods, which take into account the country-specific effects of spillovers as well as the interdependencies arising from the global diffusion of knowledge. The remainder of the paper is as follows: Section 2 presents a brief overview of the theory and empirics of knowledge spillovers.

Section 3 introduces the dataset, measurement of variables, and econometric methodology. Empirical results and discussion are given in Section 4, and the last section concludes the paper.

2. Theory and Empirics of Knowledge Spillovers

Earlier research in the literature (Griliches, 1979; Scherer, 1984; Griliches & Lichtenberg, 1984) demonstrates the promising role of knowledge diffusion in firm/industry performance, from a productivity-oriented perspective at a national level. Griliches (1992) emphasizes that apart from technological progress driven by accurate investments and strategic decisions, economic growth is unlikely to be sustained in the absence of R&D externalities, knowledge spillovers, and other inputs necessary for welfare. Besides, based on the significant level of openness and interdependencies in the global economy, knowledge tends to go beyond national borders. Coe and Helpman (1995) argue that the knowledge capital in the new economy refers to the entire world stock of knowledge rather than a specific source in a particular country. Accordingly, open economies often seek to benefit from external knowledge and technology via increasing international trade and cooperation (Cincera, Kempen, Van Pottelsberghe, Veugelers, & Sanchez, 2003).

Following the seminal work on international knowledge spillovers (Grossman & Helpman, 1990; Coe & Helpman, 1995; Lichtenberg & Pottelsberghe de la Potterie, 1998), a significant part of the recent literature also deals with the impact of spillovers from bilateral trade on productivity improvements (Halpern, Koren, & Szeidl, 2005; Acharya & Keller, 2008; Teixeira & Fortuna, 2010; Youssef & Wei, 2012; Belitz & Mölders, 2016; Dai & Chen, 2016; Fernández & Gavilanes, 2017; Nyantakyi & Munemo, 2017; Liu & Fan, 2020). Recently, the high level of economic integration between countries allows for the dissemination of a considerable amount of knowledge, mostly through spillover effects from technology investments in a particular country (Acharya & Keller, 2007). Considering the fact that developed countries are often equipped with a relatively high level of knowledge capital in the production of high-tech goods, developing economies that import heavily from these countries obtain more benefits from international trade than their counterparts with relatively low-tech trade partners (Veeramani, 2014).

Imports can affect economic performance through two common ways: learning and differentiated or more qualified inputs (Grossman & Helpman, 1991). First, imports are likely to have an enhancing effect on learning activities due to the differences between previously owned technology and imported new inputs (Kokko, 1994). Apart from relying on domestic technologies, firms also require to use external knowledge and experience, in order to ensure technological progress and bring about innovations (Dai & Chen, 2016). Second, firms with advanced foreign technologies can achieve better productivity improvement by increasing the average output per worker. Moreover, while imported technologies may be imitated by local rivals and trading partners, increasing competition based on technological advances promotes the firm motivation toward markets (Teixeiraa & Fortuna, 2010).

Several studies in the literature also refer to the importance of international R&D cooperation in explaining the diffusion of knowledge and technology by spillover effects (Cassiman & Veugelers, 1998; Cincera et al., 2003; Belderbos Carree, & Lokshin, 2004; Aschhoff & Schmidt, 2008; Barajas & Huergo, 2010). Collaborative R&D activities are regarded as an alternative tool for measuring the effects of knowledge spillovers on economic performance with a more formal framework. Cooperation between rivals, suppliers, institutions, and universities can enable the emergence of both incremental and radical innovations based on basic and applied research efforts (Belderbos et al., 2004; Aschhoff & Schmidt, 2008). R&D cooperation also provides an opportunity for firms to gain skills and experience from their research partners. A remarkable level of knowhow may emerge, be transferred and developed through the R&D initiatives of firms (López, 2008). In R&D activities, the intensity of the incoming knowledge flows is increased by the voluntary behaviors of participants. However, the complementarity relationship between R&D partners depends on the domestic technology level (Cassiman & Veugelers, 1998). Accordingly, the capacity of firms to absorb knowledge as a result of their own R&D efforts is also a measure of the ability to benefit from joint R&D with other firms (Cohen & Levinthal, 1989).

Other determining factors in the involvement of firms in R&D cooperation are related to risk and cost sharing. Collaborative agreements can sustain the high-cost R&D inputs through internal resources and external financing, as well as provide some opportunities to prevent potential risks under certain rules (Beath, Poyago-Theotoky, & Ulph, 1998). Since the firms are supposed to protect the knowledge resulting from joint research activities, R&D cooperation can weaken the involuntary knowledge flows that occur in the process of knowledge diffusion. Therefore, such cooperation can enable management of R&D spillovers in a way that maximizes the intensity of incoming knowledge by avoiding the free-riding problem that may arise from third-party firms (Cassiman, Perez-Castrillo, & Veugelers, 2002).

3. Empirical Design

The empirical part of the study investigates the effect of international knowledge spillovers via high-tech imports and R&D cooperation on economic growth. In the growth process, the study also focuses on the role of domestic knowledge stock that represents the host countries' productive capacity as well as human capital as an intermediary source of knowledge. The country group included in the analysis consists of the selected 19 countries which are emerging and developing economies according to International Monetary Fund (IMF, 2022) WEO Groups and Aggregates list. Over a wide geography, the dataset involves six countries from East Asia (China, India, Indonesia, Malaysia, Philippines, Thailand), five countries from the Middle East and Central Asia (Saudi Arabia, Kazakhstan, Pakistan, Egypt, Morocco), five countries from Latin America and the Caribbean (Argentina, Brazil, Colombia, Mexico, Peru), two countries from Europe (Russia, Turkey) and one country from Sub-Saharan Africa (South Africa). The selection of the country group is based on the availability of data used in the calculation of spillover variables and the time dimension suitable for balanced panel data.

In the analysis, the reference country group as the source of knowledge spillovers is the group of high-income OECD countries consisting of 35 members. There are several reasons for selecting this country group. Firstly, as of 2019, the share of the OECD group in the world GDP is approximately 61.5%, which has a total income of 87.7 trillion US$ in current prices (World Bank, 2022a). Secondly, according to the author's calculation based on the Eurostat (2020) classification, more than half of the world's high-tech product exports (approximately 50.6%) were performed by OECD countries in 2019 (World Bank, 2022b). Thirdly, in the same year, it is seen that 42.4% of the worldwide direct and PCT national phase patent applications belonged to the OECD group (World Intellectual Property Organization [WIPO], 2022). Based on this, it is concluded that the OECD group has an important function in wealth creation and international diffusion of knowledge. Lastly, a significant portion of the country-level data used to measure knowledge spillovers is only available in the OECD database.

3.1. Dataset and Measurement of Variables

All the data in the analysis is compiled from various official databases as well as the author's calculation for the 1995-2019 period. A total of five variables used in the analysis are given in Table 1. The dependent variable is the Gross Domestic Product per capita (*GDPpc*) as a common measure of economic growth. This variable is obtained from the World Bank (2022a) WDI database in constant 2015 US$.

Table 1: List of Variables

	Acronym	Definition	Source
D.V.	GDP_{pc}	Gross Domestic Product per capita (constant 2015 US$)	World Bank (2022a)
I.V.	*HTI*	Knowledge spillovers via high-tech imports	Eurostat (2020); WIPO (2022); World Bank (2022a, 2022b); author's calculation
	RDC	Knowledge spillovers via international R&D cooperation	OECD (2022); author's calculation
	DKS	Domestic Knowledge Stock	WIPO (2022); author's calculation
	HUC	Human Capital	UNDP (2022)

The measurement approach of spillover variables is based on the studies of Coe and Helpman (1995), Lichtenberg and Pottelsberghe de la Potterie (1998), and Belitz and Mölders (2016). In a seminal study, Coe and Helpman (1995) examine the effect of the R&D capital of a host country and its trade partner on productivity growth. The R&D capital (expenditures) as a stock of knowledge transmitted by international trade from a foreign source can contribute to the productivity level of the host country by enabling more efficient use of resources. In addition, the domestic stock of knowledge may increase the country's opportunity to benefit from the technical advances in the outside world and provides productivity improvements. Following the alternative measures proposed by Coe and Helpman (1995) and Belitz and Mölders (2016), the calculation of both domestic and foreign knowledge stock is given in equation (1).

$$KS_t = \sum_{t-1}^{t_0} (1-\delta) Pat + Pat_t \qquad (1)$$

In equation (1), the knowledge stock (*KS*) for the time 't' is measured by international patent applications depreciated by (δ) for 't-1' period. Patent data were obtained from WIPO (2022) IP data center using direct and PCT national phase patent statistics available as of 1980. Cumulative patent data from 1980 onwards were calculated by the PIM with a depreciation rate (δ) of 15% suggested by Coe and Helpman (1995). The use of patent applications instead of R&D expenditures in the measurement of stock variables is mainly based on two reasons. Firstly, patents as an ultimate output of R&D activities may allow more direct observation of the impact of knowledge on economic activity. Secondly, there are many missing/unobservable data in R&D expenditure statistics at the international level, particularly for developing countries.

The first spillover variable aims to measure knowledge flows arising from technological products of which the manufacturing involved a high intensity of R&D. Regarding the technology transfer and knowledge-intensive externalities provided by international trade, foreign knowledge embodied in imported goods from countries with a relatively high stock of knowledge can make a remarkable contribution to productivity and economic performance of host countries (Grossman & Helpman, 1990, 1995; Halpern et al., 2005, 2015; Acharya & Keller, 2007, 2008; Teixeira & Fortuna, 2010; Nyantakyia & Munemo, 2017). Accordingly, the degree of spillovers depends on the volume of trade as well as the composition of traded goods (Youssef & Wei, 2012; Dai & Chen, 2016; Fernández & Gavilanes, 2017). Following Lichtenberg and Pottelsberghe de la Potterie (1998), the calculation of the variable is given in equation (2).

$$HTI_{ij_t} = \sum_j \frac{imp_{ij_t} KS_{b_{jt}}}{Y_{jt}} \tag{2}$$

In equation (2), knowledge spillover from country 'j' (OECD group) to host country 'i' transmitted via high-tech imports channel in 't' time (*HTI*) is the trade volume of country 'i' (*imp*) relative to the income of country 'j' (*Y*), weighting by the knowledge stock of country 'j' (*KS*). The basic assumption for the measurement is that the higher the trade volume relative to the income of the exporting country, the greater the host country will benefit from foreign knowledge (Lichtenberg & Pottelsberghe de la Potterie, 1998). Imports data are compiled from the World Bank (2022b) WITS database considering the Eurostat (2020) classification for high-tech aggregation of products by SITC Rev.3. All the economic data used to calculate the variable are expressed in US$ in current prices.

The second spillover variable is measured by international cooperation in R&D activities. R&D cooperation can result in increased economic returns by enabling knowledge flows between partner firms and countries through learning processes and innovations (Barajas & Huergo, 2010). Accordingly, the profitability of such cooperation depends on the intensity of the knowledge flows transmitted through the R&D channel (Cassiman & Veugelers, 1998). The measurement method based on Belitz and Mölders (2016) is as in equation (3).

$$RDC_{ij_t} = \sum_j Pat_{ij_t}^{coop} \tag{3}$$

In equation (3), knowledge spillover arising from R&D cooperation (*RDC*) is measured by patents with foreign co-inventor/s which refers to the number of patents invented by a resident of country 'i', with at least one inventor from country 'j'. Data on patent statistics are compiled from the OECD (2022) database by priority date.

Another explanatory variable in the analysis is domestic knowledge stock (*DKS*) calculated for each of the panel countries by the same method given in equation (1). As suggested by new growth models (Romer, 1986; Lucas, 1988; Grossman & Helpman, 1991; Aghion & Howitt, 1992), domestic knowledge can result in significant increases in economic performance, often through advanced technologies involved in new products, services, or processes. Moreover, domestic knowledge can foster the ability of firms or countries to acquire, identify and use of knowledge from outside sources. Accordingly, the degree of knowledge and technology at a local level reflects the knowledge absorption capacity that ensures the efficient inward transmission of foreign knowledge (Cohen & Levinthal, 1989; Lane et al., 2001). Therefore, the improvements in the absorptive capacity may increase the beneficial use of knowledge spillovers (Grünfeld, 2003; Fernández & Gavilanes, 2017). In other words, the magnitude of the dynamic effects of knowledge spillovers also depends on the cumulative accumulation of knowledge in the historical process (Döring & Schnellenbach, 2006). Considering the decisive role of knowledge absorption capacity in the degree of benefiting from external R&D (López, 2008), the study also examines the relationship between domestic knowledge stock and R&D cooperation on the axis of knowledge spillovers. The details of the measurement procedure are given in the next section.

The last variable included in the analysis is human capital (*HUC*) as a complementary factor in the use and creation of knowledge. Based on the fact that the most common measures of human capital are related to educational indicators (Barro & Lee, 2001, 2012), this variable is compiled from the expected years of schooling data in the Human Development Index released by the UNDP (2022).

3.2. Econometric Model and Preliminary Tests

The study examines the effects of knowledge spillovers on economic growth through a base model in logarithmic form. The left-hand side of equation (4) represents the GDP per capita, while the constant term (γ), explanatory variables in table 2, and error term (ε) is given on the right side.

$$\ln GDP_{pc_{it}} = \gamma + \beta_1 \ln HTI_{it} + \ln RDC_{it} + \ln DKS_{it} + \ln HUC_{it} + \varepsilon_{it} \quad (4)$$

As mentioned in Section 3.1, the relationship between knowledge spillovers arising from R&D cooperation (*RDC)* and domestic knowledge stock (*DKS*) is examined by an additional model with interaction term [*ln(RDCxLKS)*] included in the base model. In the formation of the interaction term, both variables are transformed by centering on the mean.

The first step of the analysis involves some diagnostic and specification tests conducted for the selection of a suitable econometric method. In panel data analysis, economic shocks that occur as a result of the decisions taken by one of the cross-section units may lead to dependencies that affect the behavior and preferences of other units. In a limited time, an analysis framework that does not consider such dependencies causes measurement bias and inconsistency in estimations (Hsiao, 2007). In this regard, the results of the cross-section dependence tests suggested by Breusch and Pagan (1980), Pesaran (2004), and Pesaran, Ullah and Yamagata (2008) are given in table 2. All test statistics reject the null hypothesis of cross-section independence in the model at the 1% significance level. Another important issue in panel data analysis is whether the slope coefficients of the cross-sections are homogeneous. In general, the unconditional adoption of an assumption based on the homogeneity of the panel can lead to misleading results and therefore invalid inferences within the scope of the dataset (Phillips & Sul, 2003). Therefore, table 2 also reports the Delta test results proposed by Pesaran and Yamagata (2008). In table 2, the Δ_{adj} statistic is preferred for a relatively large dataset, while the Δ statistic is used in small samples. According to both test statistics, it is deduced that the slope coefficients specific to the cross-sections of the panel are heterogenous at the 1% significance level.

Table 2: Cross-section Dependence and Homogeneity Tests Results

Cross-section Dependence Tests					
	Test statistic	**p-value**	**Test**	**Test statistic**	**p-value**
LM (Breusch & Pagan 1980)	490.102	.000	CD (Pesaran 2004)	9.833	.000
CD_{LM2} (Pesaran 2004)	17.255	.000	LM_{adj} (Pesaran et al., 2008)	16.354	.000
Slope Homogeneity Tests					
$\tilde{\Delta}$	19.757	.000	$\tilde{\Delta}_{adj}$	22.527	.000

Notes: The test procedure was performed by Gauss 10.

Another test performed in the analysis examines the stationarity properties of the time dimension of the variables. In the case of cross-section dependence, the second-generation unit root tests can provide robust results for both the overall panel and cross-sections (Westerlund, Hosseinkouchack, & Solberger, 2016). The most common of these tests are the Cross-sectionally Augmented Dickey-Fuller test (CADF) and Cross-sectionally Augmented IPS test (CIPS) proposed by Pesaran (2007). Based on the fact that the heterogeneous characteristics of slope coefficients in the model, the CADF statistics specific to the countries in the panel are reported in table 3. The results of the model with a constant show that the level series are I(0) in some of the countries, while the others become I(1) in the first differences.

Table 3: CADF Unit Root Test Results

Country	**lnGDPPC**	**ΔlnGDPPC**	**lnHTI**	**ΔlnHTI**	**lnRDC**	**ΔlnRDC**	**lnDKS**	**ΔlnDKS**	**lnHUC**	**ΔlnHUC**
Argentina	-0.842 (6)	-3.433 (0)	-1.846 (0)	-3.655 (1)	-3.904 (1)	-6.120 (1)	-3.088 (2)	-1.365 (4)	-3.387 (4)	-3.667 (3)
Brazil	-1.282 (1)	-3,896 (0)	-4.172 (5)	-3.261 (0)	-5.234 (0)	-5.716 (1)	-1.987 (4)	-4.409 (4)	-1.515 (0)	-4.504 (0)
China	-1.605 (5)	-3.077 85)	-3.195 (3)	-3.484 (0)	-1.424 (1)	-3.093 (1)	-0.371 (3)	-3.529 (3)	-4.253 (4)	-0.615 (2)
Colombia	-4.927 (5)	-5.001 (0)	-2.426 (0)	-3.675 (1)	-3.767 (1)	-5.806 (1)	-3.808 (1)	-3.228 (0)	-8.155 (5)	-4.179 (0)

Egypt	-5.384 (1)	-2.622 (1)	-1.994 (0)	-4.943 (0)	-4.302 (0)	-5.850 (1)	-1.959 (3)	-5.436 (1)	-0.943 (0)	-3.201 (0)
India	-1.023 (0)	-3.510 (0)	-2.404 (0)	-5.152 (0)	-2.922 (0)	-5.021 (1)	-5.591 (4)	-2.163 (4)	-1.507 (1)	-3.022 (0)
Indonesia	-5.967 (2)	-3.825 (0)	-4.548 (2)	-3.297 (0)	-5.022 (1)	-6.088 (1)	-0.351 (3)	-3.605 (1)	-1.485 (0)	-5.495 (0)
Kazakhstan	-1.859 (1)	-3.108 (1)	-5.850 (2)	-4.171 (1)	-5.026 (0)	-9.440 (0)	-1.377 (2)	-3.253 (1)	-3.012 (1)	-1.835 (0)
Malaysia	-0.698 (0)	-4.940 (0)	0.129 (0)	-4.270 (0)	-4.615 (1)	-7.209 (1)	-3.853 (4)	-2.152 (1)	-2.915 (0)	-3.290 (4)
Mexico	-5.302 (2)	-4.767 (2)	-3.109 (2)	-3.128 (1)	-2.128 (1)	-6.691 (0)	-5.101 (4)	-1.965 (4)	-3.338 (2)	-4.430 (2)
Morocco	-4.184 (0)	-12.35 (0)	-2.620 (1)	-4.862 (0)	-3.999 (0)	-6.103 (0)	-3.505 (4)	-2.911 (0)	-5.472 (3)	-3.408 (0)
Pakistan	-3.075 (5)	-2.123 (1)	-3.124 (3)	-3.525 (0)	-4.995 (1)	-4.114 (1)	-2.699 (4)	-3.138 (0)	-3.883 (4)	-2.747 (0)
Peru	-2.409 (0)	-3.773 (0)	-1.988 (0)	-4.111 (1)	-4.570 (0)	-5.758 (1)	-3.849 (3)	-3.411 (2)	-1.820 (0)	-3.433 (3)
Philippines	-3.107 (6)	-1.988 (6)	-4.514 (0)	-4.322 (1)	-5.152 (1)	-6.100 (1)	-3.609 (1)	-3.119 (1)	-0.335 (1)	-4.851 (0)
Russia	-3.094 (1)	-3.341 (0)	-6.123 (1)	-5.551 (1)	-6.350 (1)	-4.748 (1)	-1.474 (2)	-3.075 (1)	-1.886 (0)	-4.080 (0)
Saudi Arabia	-4.851 (5)	-5.556 (0)	-23.71 (2)	-11.251 (1)	-3.049 (0)	-6.747 (1)	-0.301 (2)	-3.082 (0)	-3.485 (4)	-2.754 (2)
South Africa	-4.462 (6)	-4.792 (6)	-3.187 (5)	-2.990 (1)	-4.765 (0)	-10.21 (0)	-4.791 (3)	-3.034 (3)	-3.975 (3)	-3.259 (1)
Thailand	-4.235 (2)	-4.066 (0)	-4.186 (2)	-4.677 (0)	-2.719 (0)	-7.002 (0)	-2.728 (4)	-3.503 (1)	-2.879 (0)	-6.564 (0)
Türkiye	-3.065 (3)	-4.471 (0)	-3.403 (0)	-3.875 (1)	-4.311 (1)	-5.336 (1)	-3.318 (1)	-2.002 (2)	-2.119 (0)	-5.462 (0)

Notes: The test procedure was performed by EViews 12. A maximum number of lags is set to 6 and the optimal lag length determined by the Akaike info criterion is given in parenthesis. Interpolated critical values of CADF test for [T/N=25/19] are approximately -4.24 for 1%, -3.39 for 5% and -2.99 for 10% significance levels.

In the last step, the existence of long-run relationships between the variables is investigated for both the overall panel and country levels. Under the cross-section dependence and stationarity at different levels, Westerlund (2008) suggests the Durbin-Hausman panel cointegration test, which has several advantages in regard to other panel cointegration methods. The only prerequisite for the test is that the dependent variable is not stationary at the level series. That is, the existence of at least one unit root in the system is required (Westerlund, 2008).

Table 4: Durbin-Hausman Cointegration Test Results

DHg:	6.571***	*DHp:*	2.286***
Critical Values			
1%	2.330		
5%	1.645		
10%	1.280		

Notes: The test procedure was performed by Gauss 10 based on the model with constant. *** indicates the 1% significance level.

According to the panel cointegration test statistics in Table 4, the null hypotheses of no cointegration relationship between the variables of the model is rejected for both the overall panel and the country level at the 5% and 1% significance levels, respectively. Based on the findings obtained from the preliminary tests, the details of the econometric method used in the estimation are given in the next subsection.

3.3. Estimation Method

In panel data analysis, ignoring the cross-section and time-specific properties of the variables can lead to some biased and inconsistent results in estimations. Regarding the second-generation methods in the literature, Pesaran (2006) suggests the Common Correlated Effects Mean Group (CCE-MG) estimator that allows for parameter heterogeneity under cross-section dependence, while the presence of unobservable common factors is explained by the inclusion of cross-sectional means of dependent and independent variables in the regression. In this context, the coefficients are estimated for each cross-section using the parameters obtained as a result of the interaction of cross-section averages with cross-section-specific dummy variables (Pesaran, 2006; Eberhardt & Teal, 2010).

Another second-generation method in panel data analysis is the Augmented Mean-Group (AMG) estimator proposed by Eberhardt and Bond (2009) and Eberhardt and Teal (2010). In general, the AMG has the characteristics of a dynamic estimator that takes into account the cross-section dependence and parameter heterogeneity, as well as the heterogeneous structure resulting from factor loadings compared to the CCE estimator. This estimator also provides effective results in the presence of the endogeneity problem arising from the error term and in estimating the unbalanced panel (Eberhardt & Bond, 2009).

4. Results and Discussion

Results of the CCE-MG and AMG estimations with robust standard errors for the overall panel are reported in table 5. At first glance, all coefficients of the explanatory variables in the base model are positive and significant within the CCE-MG estimator. Although the AMG estimation provides similar results for the base model, there is no notable effect of *RDC* and *HUC* on economic growth. In the base model, domestic knowledge stock has a greater contribution to growth compared to the rest of the variables excluding *HUC*, whereas its significance level decreased in the AMG estimation. This result is in line with the past evidence related to productivity growth obtained by Coe and Helpman (1995), Lichtenberg and Pottelsberghe de la Potterie (1998), Teixeira and Fortuna (2010), and Belitz and Mölders (2016). Similarly, it is concluded from the base model that knowledge spillovers via high-tech imports have a significantly positive impact on long-run growth. This result is also consistent with the findings of Acharya and Keller (2008) regarding productivity improvements. However, the positive effect of knowledge spillovers via R&D cooperation is weak in the base model. Lastly, the coefficient of *HUC* provides partial evidence of the growth-enhancing effect of human capital.

Regarding the model with interaction term in table 5, the coefficient of *HTI* confirms the evidence from the base model that knowledge spillovers via high-tech imports are a prominent determinant of growth in emerging and developing economies. Although the main effects of *DKS* and *RDC* are positive in both estimations, the latter is statistically insignificant. However, the weak effect of *RDC,* which is conditional to *DKS,* can be associated with the deficiencies in the knowledge absorption capacity related to domestic knowledge stock in developing economies. This result supports the both theoretical and empirical implications of various studies (Jaffe, 1986; Cohen & Levinthal, 1989; Lane et al., 2001; Gorodnichenko et al., 2007; Fernández & Gavilanes, 2017).

Table 5: Overall Results of CCE-MG and AMG Estimations

	CCE-MG				AMG			
lnGDPPC	Base Model		Model with Interaction Term		Base Model		Model with Interaction Term	
	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.
Cons.	-.004	1.116	-.391	1.151	6.854***	.682	7.518***	.556
lnHTI	.031**	.014	.040***	.014	.035*	.019	.039**	.019
lnRDC	.007**	.003	.011	.013	.001	.006	.000	.017
lnDKS	.113***	.044	.102*	.061	.068*	.036	.079**	.040
lnHUC	.395**	.171	.329*	.178	.144	.203	.122	.186
ln(RDCxLKS)			.003	.015			.032**	.016
_cdp			.811***	.113			.734***	.107
Wald test	$\chi^2(4)$:22.16***		$\chi^2(5)$:14.59**		$\chi^2(4)$:7.57*		$\chi^2(5)$:12.90**	

Notes: The results are obtained by Stata 14.2 with the xtmg command. *_cdp* refers to the common dynamic process. ***, ** and * indicate the significance levels at 1%, 5% and 10%, respectively.

In the AMG estimation, the coefficient of the interaction term is positive and statistically significant, while it increased considerably compared to the CCE-MG estimation. Thus, it is concluded that the impact of knowledge spillovers via R&D cooperation on economic growth increases significantly, depending on the improvements in domestic knowledge stock. In other words, knowledge absorption capacity at a national level is an important determinant of the beneficial use of knowledge spillovers via R&D cooperation in emerging and developing economies. This result also provides a complementary contribution to the productivity-oriented evidence reached by Belitz and Mölders (2016). In addition, both estimations reach the same results as the base model for the coefficient of *HUC*. Finally, the coefficients of the common dynamic process (*_cdp*) in the AMG estimation indicate that some joint factors contribute significantly to economic growth but cannot be observed within these models. The Wald statistics of all the estimations verify the goodness of fit for both models.

The country coefficients of CCE-MG and AMG estimations are given in table 6. In the base model, the coefficient of *HTI* is positive in 13 countries but significant in 8 of them (Argentina, Brazil, Colombia, Indonesia, Mexico, Pakistan, Peru, and

South Africa). In the AMG estimation, *HTI* is negative and significant for Morocco and Russia in the CCE-MG estimation and the same is true for India and Malaysia in the AMG estimation. In addition, this coefficient turns out to be positive for Morocco, while it becomes insignificant for Russia in the AMG estimation. The coefficient of *RDC* in the same model is positive in 12 countries, but only significant for Indonesia, Malaysia, and South Africa. However, only the significantly negative coefficient is obtained for Indonesia in both estimations. The coefficient of domestic knowledge stock (DKS) is positive in 14 countries, while 9 of them are statistically significant. Contrary to this, the same coefficient is negative and significant in Mexico, Pakistan, and Peru in both estimations. Lastly, the results of the base model show that the coefficient of *HUC* is positive in 14 countries, whereas countries with significant coefficients are Kazakhstan, Mexico, Morocco, Pakistan, Peru, Philippines, and Russia.

Table 6: Group Results of CCE-MG and AMG Estimations

CCE-MG									
	Base Model				**Model with Interaction Term**				
	lnHTI	**lnRDC**	**lnDKS**	**lnHUC**	**lnHTI**	**lnRDC**	**lnDKS**	**lnHUC**	**ln(RDCxLKS)**
ARG	.122***	.009	.078	-.305	.112***	.020	.039	-.183	-.072
BRA	.098***	.015	.298*	-.105	.085**	-.017	.271	-.006	.035
CHA	-.009	-.012	.186	1.121	.103***	-.193***	-.411**	3.438***	.076***
COL	.047***	-.002	.278***	-.109	.043**	.008	.266***	-.094	.007
EGP	-.005	-.014	.275***	-.630**	-.023	.048	.380***	-.724**	.067**
IND	-.011	-.052	-.105	.095	.002	-.060	-.165	.082	.019
INS	.054**	.016*	.156	.326	.064***	.002	.070	.087	-.024
KAZ	.007	-.001	.195**	1.906***	.014*	.073	.370**	1.724***	.077
MLY	-.039	.024**	.154*	.082	-.041	.022**	.101	-.133	-.041
MEX	.195***	.023	-.275**	1.615***	.202***	.008	-.219	1.748***	.009
MOR	-.035**	.003	.118***	.553**	-.039*	-.005	.116**	.524**	-.004
PAK	.029***	.007	-.090*	.647***	.034***	-.099***	-.239***	.513***	-.068***
PRU	.094***	-.002	-.120*	.054	.085***	.048	-.049	-.009	.035
PHP	.017	.000	.074	.456	.025	.017	.088	.532	.049
RUS	-.022**	-.005	.541	1.250***	-.023**	.360	.698*	1.038**	-.177
SAU	-.005	.018	.101***	1.256	-.006	-.064	.170***	1.102	-.047
SAF	.044	.015	-.024	.346	.043**	.241**	.242	1.040**	-.350*
THA	.031	.012	.284**	-.163	.044	.045	.260*	-.324	-.037
TUR	.087	.029	.025	.092	.107*	.067	-.012	-.024	.061

AMG									
	Base Model				Model with Interaction Term				
	lnHTI	lnRDC	lnDKS	lnHUC	lnHTI	lnRDC	lnDKS	lnHUC	ln(RDCxLKS)
ARG	.114***	.018	.319***	-1.40***	.120***	.008	.335***	-1.21***	.068
BRA	.148***	.002	-.043	-.257**	.134***	-.093***	.003	-.564***	.099***
CHA	-.018	.047	.230***	.606	-.013	.045	.222**	.551	.001
COL	.082***	-.012	.068	-1.16***	.034	.128***	.129*	-.432	.111***
EGP	.009	.030	.269**	.089	.020	-.033	.152	.058	-.055
IND	-.129***	.096***	.085	-.651	-.107	.084**	.033	-.714	.022
INS	.022	-.049*	.039	.629	.048	-.005	.327*	.711	.117**
KAZ	.000	-.001	.314***	2.162***	.000	-.027	.253*	2.069***	-.027
MLY	-.144***	.004	.114	-.027	-.15***	.006	.121	-.051	.012
MEX	.176***	.004	-.362***	1.277***	.172***	.027	-.377***	1.302***	-.023
MOR	.030	.001	-.018	.340**	.009	-.056	-.017	.306**	-.029
PAK	.016*	.008	-.040***	.716***	.032***	-.094***	-.182***	.527***	-.066***
PRU	.086***	.002	-.038**	.331**	.087***	.036	.021	.312**	.023
PHP	-.002	-.021	.074	1.489***	.004	.003	.126	1.529***	.051
RUS	-.021	-.042	.951***	-.496	-.021	-.042	.949**	-.502	-.001
SAU	-.002	.001	-.019	-.375	-.005	.074	-.060*	.006	.035
SAF	.105***	.040**	.123	-.065	.103***	-.126	-.030	-.181	.295
THA	.035	-.007	-.054	.126	.076	-.012	.068	.000	.103*
TUR	.060	-.020	.045	.145	.108**	.071*	.094	-.262	.078***

Notes: The results are obtained by Stata 14.2 with the xtmg command. ***, ** and * indicate the significance levels at 1%, 5% and 10%, respectively. ARG: Argentina, BRA: Brazil, CHA: China, COL: Colombia, EGP: Egypt, IND: India, INS: Indonesia, KAZ: Kazakhstan, MLY: Malaysia, MEX: Mexico, MOR: Morocco, PAK: Pakistan, PRU: Peru, PHP: Philippines, RUS: Russia, SAU: Saudi Arabia, SAF: South Africa, THA: Thailand, TUR: Türkiye.

In the model with the interaction term, the number of countries with a positive coefficient of *HTI* is the same as in the base model, while the number of those with significant *HTI* increases to 11 in the CCE-MG estimation. In addition, when compared with the base model, it is observed that the coefficients of China and Türkiye turn positive and significant in both estimations. The main effect of *RDC* is positive in 13 countries, but only significant in Colombia, Indonesia, Malaysia, South Africa, and Türkiye. This coefficient is positive for Türkiye in the AMG estimation. However, the main effects significantly turn negative for Brazil in the AMG estimation and for China in the CCE-MG estimation, while the same is true for Pakistan in both estimations. Similarly, the main effect of *DKS* is positive in 14 countries but significant in 7 of them. Interestingly, this coefficient becomes significantly negative for China in the CCE-MG compared to the AMG estimation.

Moreover, the interaction effect of China is significantly positive in the same estimation. In contrast with this result, the coefficient of *DKS* for Pakistan is also significantly negative, while the same is true for the interaction effect in both estimations. Considering the negative signs of *RDC* in both countries, the interaction effects can be explained by the level of domestic knowledge stock or the intensity of incoming spillovers. The first would be valid for Pakistan, while the latter would be true for China. It is also concluded that 6 of the coefficients of the interaction term in the rest of the countries (Brazil, Colombia, Egypt, Indonesia, Thailand, Türkiye) are significantly positive. In addition to Pakistan, the interaction effect of South Africa is negative and significant at the 10% significance level. Finally, the effect of *HUC* on economic growth is positive in 14 countries, whereas it is significant in 8 of them (China, Kazakhstan, Mexico, Morocco, Pakistan, Peru, Philippines, Russia, and South Africa).

5. Conclusion

Along with the widespread effect of globalization, domestic knowledge tends to become a part of the entire stock of knowledge in the world through spillover effects transmitted by various channels. In the new economy, cross-country growth differences mostly arise from the beneficial use of external knowledge embodied in qualified inputs as well as learning effects based on the adaptation and imitation of foreign technologies. These differences are more evident in the knowledge and technology-intensive economic activities carried out by a small number of developed countries. The results of the study demonstrate that knowledge spillovers via high-tech imports are a prominent determinant of long-run economic growth. Emerging and developing countries seem to benefit from the knowledge stock of advanced economies in the development of the local technology level and the emergence of innovations. The results also confirm the growth-enhancing effect of the domestic knowledge stock as a measure of knowledge absorption capacity. A relatively high degree of absorptive capacity may enable to better exploit externalities arising from global knowledge in local production chains. However, it is deduced that the knowledge spillovers via R&D cooperation have alone weak and somewhat insignificant positive impact on economic growth. This result is associated with the complementary relationship between incoming R&D spillovers and the knowledge absorption capacity of countries. Accordingly, the results indicate the essential role of increasing absorptive capacity in gains from international R&D spillovers. Therefore, a sufficient level of domestic knowledge stock can improve the intensity of incoming knowledge from collaborative R&D activities.

Consequently, emerging and developing countries are likely to achieve their long-run economic goals through diversifying the transmission channels that provide effective access to global knowledge, as well as increasing the domestic stock of knowledge, and thus the absorptive capacity at a national level.
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Appendix

Table 1a: Country Group included in the Analysis

1.	Argentina	6.	India	11.	Morocco	16.	Saudi Arabia
2.	Brazil	7.	Indonesia	12.	Pakistan	17.	South Africa
3.	China	8.	Kazakhstan	13.	Peru	18.	Thailand
4.	Colombia	9.	Malaysia	14.	Philippines	19.	Türkiye
5.	Egypt	10.	Mexico	15.	Russia		

Table 2a: Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
lnHTI	475	7.013571	1.426778	0	10.75878
lnRDC	475	3.198584	1.677133	0	8.120886
lnDKS	475	10.12436	1.463748	7.234971	15.68702
lnHUC	475	2.502689	.2260718	1.588773	2.908987
ln(RDCxLKS)	475	2.100245	3.711934	-2.637778	27.38109