Article:
Le, T, Pham, H orcid.org/0000-0002-0764-9182, Mai, S et al. (1 more author) (2022) Frontier academic research, industrial R&D and technological progress: The case of OECD countries. Technovation, 114. 102436. ISSN 0166-4972

https://doi.org/10.1016/j.technovation.2021.102436

To cite this article, please follow: Le, T., Pham, H., Mai, S. and Vu, N. (2021). Frontier academic research, industrial R&D and technological progress: The case of OECD countries. *Technovation.* https://doi.org/10.1016/j.technovation.2021.102436

Frontier academic research, industrial R&D, and technological progress: the case of OECD countries

Abstract

Since frontier academic research is often thought to be driven by recognition and promotion rather than commercial values, its real contribution to a country's technological progress is sometimes doubted. Against this skepticism, this paper argues that frontier academic research resembles a public good and creates important scientific foundations for industrial innovation. When diffused to industry, it significantly contributes to the country's technological improvement. Using panel OLS and dynamic panel OLS estimation methods to analyze a dataset of 18 OECD countries during 2003-2017, this paper finds substantial support to this theory. Obtained results indicate that both frontier academic research and industrial R&D are beneficial to a country's technological progress, but a large proportion of the effect of frontier academic research on a country's technological development is transferred through industrial R&D. In countries with relatively abundant industrial R&D, frontier academic knowledge becomes relatively less attractive in production. These results are robust across different estimation methods, regression specifications, and different proxies of frontier academic research and technological progress. They convey important implications for policymakers in designing national strategies towards promoting a nation's long-term technological development.

Keywords: Total factor productivity; Frontier academic research; Industrial R&D; Mediation analysis.

JEL classification: O31, O33, O47.

1. Introduction

Seminal literature on research and development (R&D) and economic growth (e.g., Aghion and Howitt, 1992; Grossman and Helpman, 1991; Romer, 1990) proposes that technological progress[1] differs across countries mainly due to cumulative R&D experience. While this proposition comes clear with industrial R&D, the role of scientific/academic research in promoting technological development is often less straightforward. Specifically, there exists empirical evidence on university research spilling into inventions and innovations by private firms (e.g., Acs *et al.,* 1992; Cohen *et al*., 2002; Jaffe, 1989; Mansfield, 1991, 1998), whereas a few others cast doubts about the benefit of scientific research to industrial innovation. For example, Gittelman and Kogut (2003) report a negative relationship between scientific capabilities and innovation efforts, implying that scientific knowledge does not necessarily generate high-impact industrial innovations. Even though the industry might need scientific knowledge from academia to tackle technological problems or exploring new projects, the 'taste of science'[2] of the researcher can create a gap between science that is considered as beneficial for firms' innovation and those that are perceived as valuable by the scientific community (Gittelman and Kogut, 2003). Also, it is speculated that the primary objective of academic research is to achieve recognition and promotion in academia rather than commercial values (Dasgupta and David, 1994). The competition for publications might involve certain tactical activities, such as squeezing ideas into publications of negligible contributions to the advancement of science or having an extremely large co-authorship. The policy nurturing such type of 'academic fame' can redirect talented researchers from doing research that is meant to make real economic

[1] This term is widely used in innovation economics and management literature to indicate innovation and productivity improvement.

[2] The term 'taste of science' refers to the intrinsic motivation of a scientist to conduct a specific research direction (Gittelman and Kogut, 2003).

contributions to the one that is simply for the sake of publications (Aguinis *et al.,* 2020). All these suggest that the debate on the benefit of academic research, especially research at frontier level, to technological development remains a controversial topic.

To provide an improved knowledge on this matter, this paper examines if frontier academic research has real effects on a country's technological progress and, if so, the mechanisms through which these influences occur. Drawing from new growth theory (e.g., Aghion and Howitt, 1992; Grossman and Helpman, 1991; Romer, 1990), we conceptualize two main economic mechanisms through which frontier academic knowledge induces technological changes. *First,* through publications in scientific journals, the practical discoveries by frontier academic research can help improve large-scaled production processes and management methods. *Second,* the indirect effect of frontier academic research on technological progress is mediated by industrial R&D that occurs in the form of knowledge transfer from universities to firms. Specifically, the knowledge contained in academic publications can be transferred from academic researchers to their industrial counterparts through a university-industry partnership; or to their university students who, upon graduation, become entrepreneurs or industrial researchers. These people will help transform knowledge codified in academic publications into commercial innovation.

We choose to use the data from OECD countries for our empirical analysis. This is because OECD countries have been the cradle of scientific inventions and a world leader in innovation and productivity. They are also the pioneering countries that appreciate the prominent role of higher education institutions in enabling the creation and development of industrial clusters and promoting regional and national development.[3]

Specifically, we use the data from 18 OECD countries during 2003-2017. We use Aiken and West's (1991) method on interaction effect analysis and Baron and Kenny's (1986) method on

[3] The lack of data on R&D (either missing or non-existent) in developing countries makes it difficult to conduct research on these countries. So far, existing studies have mostly considered R&D spillovers from OECD countries to developing countries (e.g., Coe and Helpman, 1997; Le, 2010, 2012). When it comes to dealing with R&D capital stocks of developing countries, these studies choose to ignore those terms in their regressions.

mediation analysis to examine the direct and indirect effects that frontier academic research may exert on technological progress. Our panel-based approach captures both time series and cross-sectional dynamics between frontier academic knowledge, measured by aggregate research scores of leading universities, and total factor productivity (TFP), as a proxy for technological progress, with industrial R&D being the mediation and/or moderation factor. Within that context, panel cointegration estimation is chosen to provide reliable statistical inferences.

Our results show that frontier academic knowledge significantly affects the technological progress of a country in the long run. There is an indirect effect of frontier academic knowledge on TFP that is mediated by industrial R&D investment. In other words, firms will take advantage of the frontier research knowledge made available by academia to innovate and, in turn, enhance their production. In countries with relatively abundant industrial R&D, frontier academic knowledge loses its relative attractiveness in production. Its direct effect on TFP is, therefore, weakened. This means that industrial R&D negatively moderates frontier academic knowledge. This is because these countries depend more on industrial R&D and less on frontier academic research to improve their TFP. These results are robust across alternative econometric specifications that control for country- and time-specific effects, different tests for the significance of mediation relationship between frontier academic knowledge and industrial R&D, and a range of proxies for frontier academic knowledge.

Our paper offers new insights into the real effects of frontier academic research and, hence, bridges the knowledge gaps among three literature strands. *First,* it contributes to the literature on R&D and economic growth. Prompted by Schumpeter (1911), a large amount of literature has emphasized the important role of R&D investment on economic growth over the last century, both theoretically (e.g., Grossman and Helpman, 1991; Romer, 1990) and empirically (e.g., Coe and Helpman, 1995; Luintel *et al.*, 2014). However, these studies often consider R&D as a whole without specifying different types, such as academic and industrial R&D, while it is believed that different types of R&D are likely to affect the economic development path in different ways. In our study, the impact of academic research is examined separately from industrial R&D. This approach enables a holistic view of the mechanisms through which academic research and industrial R&D induce technological progress. Obtained results highlight that frontier academic research can go beyond the pursuit of reputation or promotion in the academic sector because it can induce technological changes and, thus, makes real economic impacts. *Second*, our paper contributes to the rich literature examining the economic impact of academic research. Studies within this literature strand, such as Jensen and Thursby (2001) and Thursby and Kemp (2002), generally confirm that academic research significantly contributes to economic success. While the evidence is mainly established on university-firm linkages (e.g., Acs *et al.*, 1992; Cohen *et al.*, 2002; Jaffe, 1989; Mansfield, 1991, 1998), that on the nation-wide scale is scant. This paper fills this gap with rigorous evidence at the macro level. More importantly, our study proves that the contribution of academic research to technological advancement is largely indirect and transferred through industrial R&D. In other words, academic research may not be able to exert a significant impact on technological development without a reciprocal industrial R&D investment. *Third*, our paper adds a new measurement scale of academic research. While the majority of papers adopt R&D expenditure in the academic sector (e.g., Eid, 2012) or supercomputer computing capacity (e.g., Le and Tang, 2015) for their variables, this paper proposes the use of a brand-new measure: frontier academic research calculated based on research scores of Top 500 universities in the Academic Rankings of World Universities. This is a better proxy indicator of knowledge stock than the commonly used R&D expenditure as the mechanism to turn research input into research output is full of hurdles and uncertainties. Furthermore, using this output-based measure[4] can help avoid the problem of excessive noise (as R&D expenditure has monetary value, it is subject to fluctuations in the exchange rate, price conversion, inflation, or even depreciation).[5]

[4] Other output-based measures include patent citations by Kerr (2010). With a focus on academic publications, our academic research indicator is complementary to those patent measures. While publications largely resemble a public good, patents are considered a private good.

[5] The complication in establishing the depreciation rate of R&D assets is discussed in Li and Hall (2020).

The rest of the paper is organized as follows. In Section 2, we discuss the related literature. In Section 3, we describe our data collection, computation and provide summary statistics. In Section 4, we present our empirical strategy and report estimation results. Finally, we discuss our research findings and conclude our paper with some implications for practice in Section 5.

2. Related literature and conceptual framework

2.1. Literature on determinants of technological progress

Technological progress is the term widely used in innovation economics and management literature to indicate innovation and productivity improvement. Technological progress can be measured by the number of patents (Baba *et al.*, 2009; Jaffe, 1989; Wirsich *et al.*, 2016), an economic value associated with patents (Kogan *et al.*, 2017), innovative outputs (George *et al.*, 2002; Le and Tang, 2015), labor productivity (Eid, 2012) or TFP (Coe and Helpman, 1995, 2009; Engelbrecht, 1997; Luintel *et al.*, 2014; Kim and Park, 2017; Tsamadias *et al.*, 2019).[6] Among these measures, TFP is perhaps the most widely used measure for technological progress in a country.

Prior research suggests various determinants of technological progress that can be categorized into four groups: (i) Creation, transmission and absorption of knowledge; (ii) Factor supply and efficient allocation; (iii) Institutions, integration and invariants; and (iv) Competition, social dimension and environment (Isaksson, 2007).

Among those factors, R&D is the key determinant of technological progress as it creates the knowledge needed for technological progress. The theoretical underpinning for the R&D and technological progress nexus arises from the endogenous growth theory[7] (e.g., Romer, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1992). Indeed, based on the premise that knowledge is one of the key factors of production, endogenous growth theory posits the important role of R&D in the technological progress of a country. R&D has two 'faces' in promoting productivity

[6] Dziallas and Blind (2019) provide a comprehensive review of innovation indicators, including those potentially capturing academic research.

[7] The endogenous growth theory is also known as the new growth theory

growth: on the one hand, R&D promotes a firm's innovative potential (hence directly raising TFP growth rate); on the other hand, it improves the absorptive capacity of firms and industries, thus facilitating the adoption of new technologies and spurring technological progress (Mc Morrow *et al.* 2010). Empirical research on the role of R&D in technological progress has distinguished two types of R&D: industrial R&D and academic research.

In measuring academic research, existing empirical studies on the link between academic research and technological progress have proxied academic research with R&D expenditure (e.g., Eid, 2012; Jaffe, 1989; Le and Tang, 2015), the number of academic publications (e.g., Lundberg, 2017; Dziallas and Blind, 2019) or the number of citations to academic papers (e.g., Audretsch *et al.*, 2012; Iaria *et al.*, 2018).

Jaffe (1989), the first empirical research examining the extent to which university research spills over into the invention and innovation of private firms, uses the research expenditures undertaken at universities as a measure for academic research and the number of patented inventions as a proxy for innovation. He reports that corporate patent activities respond positively to commercial spillovers from university research in the US from 1972 to 1981. In addition, the increase of patenting activity is positively associated with R&D expenditure of private enterprises as well as research expenditure conducted by universities.

Most of the post-Jaffe empirical studies analyze the impact of academic research on innovation, productivity or growth rate of output via survey and/or microdata to explore the impact at a firm-level. For example, using data on 475 IPO firms and 66 universities in Germany between 1996 and 2007, Audretsch *et al.* (2012) measure academic research with citations and firm innovation with patenting. They find a significant impact of citations per researcher on the patenting behavior of entrepreneurial firms. Upon employing the sample of 455 active firms in photocatalysis in Japan and using the number of registered patents to measure firms' R&D productivity, Baba *et al*. (2009) report the effectiveness of university-industry collaboration on firms' innovative performance. Measuring firm innovation by the number of innovative products in the US, George *et al.* (2002) report a significant relationship between university linkages and innovative output for 147 biotechnology firms. Using the number of patents to proxy for firm innovation, Wirsich *et al.* (2016) show that joint publications between university academics and industry experts have a significant impact on the patent data of 318 technology-oriented firms during 1985–2007.

At the country aggregate level, Eid (2012) and Le and Tang (2015) are the only two studies examining the impact of academic research on a country's technological progress. Eid (2012) employs gross R&D expenditure to proxy for academic research and industrial R&D, and the average growth of real output per worker to a proxy for productivity growth. Le and Tang (2015) use academic research expenditure in terms of high-tech research investment in the supercomputer capacity to proxy for academic research and TFP to proxy for national technological progress. Both studies converge to the point that academic research strongly affects technological change.

Nevertheless, academic research is sometimes considered of little value to industrial innovation. For instance, a negative relationship between the number of scientific papers and high-impact innovations is reported in Gittelman and Kogut (2003). Their findings imply that scientific knowledge does not necessarily generate high-impact industrial innovations. One reason supporting this result is that the value perception in science and in the industry are not the same. Even though industry might need scientific knowledge to tackle technological problems or exploring new projects, the 'taste of science' (the intrinsic motivation of a scientist to conduct a specific research direction) of the researcher can create a gap between science considered as beneficial for firms' innovation and those are perceived as valuable by the scientific community (Gittelman and Kogut, 2003). Another reason attributed to this result is that the primary objective of academic researchers is to achieve recognition and promotion in academia rather than commercial values (Dasgupta and David, 1994). Indeed, the rewarding scheme at higher education, which is popularly based on the number of publications in frontier academic journals, academics' efforts to conducting research for top journal publications rather than for commercial values (Hilmer *et al.*, 2015). From this perspective, academic publications can be seen as a legitimate tool of persuasion and a symbol of achievement (Cetina, 2009; Gittelman and Kogut, 2003; Latour and Woolgar, 2013). The competition for publications might involve certain tactical activities (strategic citing and praising, squeezing publications from minor ideas, etc.), resulting in publications with insignificant contributions to the advancement of science (Binswanger, 2015). The policy nurturing this 'academic fame' can lead to misallocation of effort and resources to do research for frontier academic publications rather than for real technological progress in the industry.

In summary, our review of the empirical literature on the link between R&D and technological progress highlights the shortage of studies examining the effect of academic R&D on TFP and the inconclusive debate on the benefit of academic research, especially research at frontier level, to the technological development of a country.

2.2. The conceptual framework

Drawing from the endogenous growth theory (Romer, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1992), we develop the conceptual framework with two key hypotheses below.

2.2.1 The total effect of frontier academic research on technological progress

According to Secundo *et al.* (2017), universities undertake three key functions: (i) training human resources (education); (ii) producing new knowledge (research); and (iii) engaging with societal needs and market demands (social engagement). Although these functions have their distinct features, they are highly connected. Typically, as part of the society, universities' social engagement is mainly conducted through technology transfer and continuing education for entrepreneurial competencies as well as talent attraction and academic incubation. These diverse activities serve as important vehicles through which universities facilitate technological progress in the region and the nation where they are located. In that process, academic research clearly plays a key role in inducing technological progress since it creates new knowledge.

Indeed, academic research can give rise to technological changes in a country through education and training as education and training nurture human capital accumulation. Meanwhile, human capital is a critical source for a nation's technological progress (Schultz, 1961). Empirical evidence for the significant effect of human capital stock on TFP can be found in Coe and Helpman (1997), Engelbrecht (1997), Coe *et al.* (2009) and Luintel *et al.* (2014). Academics contribute to the development of a country's human capital through their educating and training responsibility, such as lecturing and supervising students, providing graduates and employees with vocational training (Bekkers and Freitas, 2008; Jones and de Zubielqui, 2017; Meyer-Krahmer and Schmoch, 1998; Rosenberg and Nelson, 1994; Varga, 2000; Zucker *et al.*, 2002). This literature strand hints that research-active academics may provide lectures and supervision with academic rigor and new knowledge to their students. Those activities can enhance the quality of a nation's human capital and stimulate technological progress.

Academic research can stimulate technological progress by creating new knowledge embedded in publications as well. Because of its widespread disclosure through publications in scientific journals, frontier academic research closely resembles a public good. Such practical discoveries embedded in publications can directly improve large-scale production processes and management methods in industries, raising the technological level of a country. Some studies suggest that knowledge spillovers from universities to firms can also occur through publishing scientific research in scholarly journals. As knowledge (especially in natural sciences) embedded in scientific papers can be seen as codified or explicit (i.e., knowledge developed based on a unified and established scientific methodology), it can be transferred and transmitted with low cost (Audretsch, 2013). For example, one can easily access and absorb knowledge spillovers by competently reading academic research publications that can be retrieved from the Internet, libraries or publishers. The impact of these knowledge spillovers is especially important for young and new startup firms, who have limited resources to conduct formal R&D, as they can rely on external knowledge generated by universities as an alternative. In addition to this, Audretsch and Feldman (1996) highlight the role of university research as one of the most important knowledge externalities that encourage knowledge-based industries to foster innovative activities. Previous studies report that research output by universities (measured by the number of citations) has a significant positive impact on firm innovation behaviors (measured by firms' patents). In other words, academic research is found to have a positive impact on firm innovation, hence, enhance technological change (Audretsch *et al.*, 2005; Audretsch *et al.*, 2012; Zucker *et al.*, 1998). Taking all together, we propose that:

H1: *Frontier academic research has a positive total effect on technological progress of a country.*

2.2.2 The mediating role of industrial R&D

Frontier academic research can induce industrial innovation through university-firm linkages. Pioneering research by Jaffe (1989), Mansfield (1991, 1998), Acs *et al.* (1992) indicates that technological change in some sectors of the economy has been based significantly on academic research. Most of the existing work focuses on the premise that knowledge can spill over from universities to firms through collaborations, patents, and licensing (Cohen *et al.*, 2002; Bekkers and Freitas, 2008; Mansfield, 1991, 1998; Thursby and Kemp, 2002). The university-industry R&D collaborations play a significant role in transforming academic discoveries into commercial technologies (Faulkner and Senker, 1994; George *et al.*, 2002; Markman *et al.*, 2009). Because universities may lack the capacity to commercialize radical new ideas themselves, university-industry collaborations can overcome these difficulties by facilitating access to firms, external knowledge as well as complementary resources and, ultimately, enhance knowledge diffusion between partners through collaboration (Wirsich *et al.*, 2016). From firms' perspective, collaborations with universities are imperative not only for increasing and leveraging valuable resources, such as scientists and state-of-the-art research facilities but also for exploiting scientific knowledge (Audretsch *et al.*, 2012; Liebeskind *et al.*, 1996; Pisano, 2010). For example, joint patenting with a university has a positive impact on the quality of firms' R&D in the long term (Amesse and Cohendet, 2001; Briggs, 2015; Lai, 2011). Belderbos *et al.* (2004) find that university-industry collaborations, in particular, can target more market-oriented or radical innovations. Wirsich *et al.* (2016) discover that linkages between academia and industry can drive technological novelty.

Technology transfer is another critical source of knowledge spillovers from universities to firms which helps enhance technological progress in the industry. Bekkers and Freitas (2008) indicate that university scientists provide industry researchers with a critical source of knowledge. Through direct licensing or forming a university-industry partnership, the knowledge contained in academic publications can be transferred from frontier academic researchers to their industrial counterparts (knowledge diffusion). This knowledge is also embedded in university students who, upon graduation, become entrepreneurs or industrial researchers (knowledge development). These people will help transform knowledge codified in frontier academic publications into commercial innovation, a crucial part of technological progress in a country. Therefore, we posit that:

H2: *Industrial R&D mediates the relationship between frontier academic research and technological progress.*

A sketch of our conceptual framework is provided in Figure 1. This figure also serves as a representation of the mediation analysis conducted in Section 3 below.

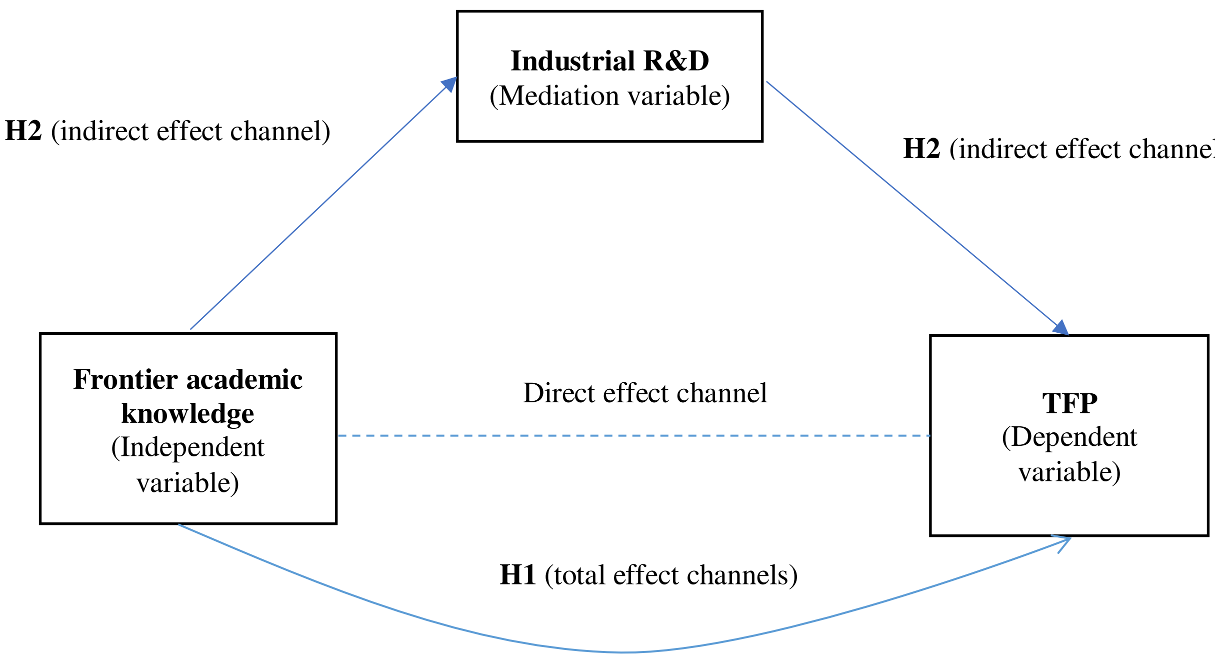

Figure 1 – The conceptual framework

3. Research methodology

3.1. Data construction and summary statistics

To examine the role of frontier academic research in enhancing technological development, we start our sample selection procedure by focusing on countries with a large number of universities listed in Academic Rankings of World Universities (ARWU) conducted by Shanghai Jiaotong University. In doing so, we choose countries that made themselves to the list over the entire 2003-2017 period. In addition, countries in the sample also need to have recorded data on industrial R&D expenditure. Based on these double criteria and due to data limitation, we have to exclude a few countries from our sample, such as Greece, Israel, or New Zealand. After making these adjustments, we finalize a panel data set that covers 18 OECD countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, Norway, Spain, Sweden, Switzerland, the United Kingdom and the United States.

3.1.1. The measure of frontier academic research

To compute the measure of total frontier academic knowledge for each country in the sample, SA_{it}, we utilize the data on the research capability of world universities known as ARWU conducted by Shanghai Jiaotong University. Together with the World University Rankings published by Times Higher Education (THE) and QS World University Rankings published by Quacquarelli Symonds (QS), ARWU is one of the most popular league tables in the world. Historically, THE and QS had a joint publication during 2004-2009 before their split in 2009. While ARWU totally focuses on research, both QS and THE take account of other aspects of higher education institutions as well, such as teaching, infrastructure and international diversity. Among those indicators used to assess the performance of universities worldwide, QS and THE also include some subjective measures, such as academic peer review and employer peer review (QS) or research reputation peer review (THE).

We choose ARWU indicator for our study ahead of the other two for two reasons. *First*, this indicator has an entire focus on research performance and a high level of objectivity. This fits well with the aim of using research capability to construct an objective stock of knowledge of this study. *Second*, ARWU offers a longer time series on universities' research performance which allows for richer and more resourceful empirical analysis. In particular, ARWU research scores are available from 2003 onwards, while this corresponding data is only available from 2011 for THE and 2012 for QS (before this time, only the rankings were made available, not the scores). Although we use ARWU indicator for our baseline models, we also run some regressions using THE data for our robustness check and include obtained results in the Appendix.

Since its first publication in 2003, the ARWU has been designed to measure universities' research strengths using the following six indicators: the number of alumni that have received Nobel prizes and Fields medals, the number of staff that have received Nobel prizes and Fields medals, the number of highly cited researchers in 21 broad subject categories selected by Thomson Scientific, the number of papers published in *Nature* and *Science*,[8] the number of papers indexed in Science Citation Index (Expanded) and Social Science Citation Index, and the per capita academic performance of these indicators. More than 1,000 universities are surveyed annually. To be included in the survey, universities must have Nobel laureates, Fields medalists, highly cited researchers, research papers published in Science or Nature, or a number of papers indexed in Science Citation Index (Expanded) and Social Science Citation Index. However, when it comes to results, only the rankings and scores accompanying the rankings of the Top 500 universities are reported. To compute the national stock of frontier academic knowledge for a representative country j in year t, SA_{jt}, we aggregate the scores underlying the rankings of all ARWU-listed universities of j as follows:

$$SA_{jt} = \sum_k Score_{kt} = \sum_k (Staff_{kt} + Alumni_{kt} + HiCited_{kt} + NS_{kt} + Pub_{kt}).$$

[8] For institutions with high specialization in humanities and social sciences, this indicator is not considered. Instead, its weight is allocated to other indicators.

Here, $Score_{kt}$ is the corresponding score of ARWU-listed university k. That score is the unweighted sum of five different research dimensions: staff being awarded a Nobel prize or Fields medal ($Staff_{kt}$), alumni being awarded a Nobel prize or Fields medal ($Alumni_{kt}$), score on highly cited researchers ($HiCited_{kt}$), score on Nature and Science publications (NS_{kt}) and score on indexed publications (Pub_{kt}). Note that in this calculation, we exclude the indicator on per academic performance because this indicator is mainly used to control for the size of universities, hence, probably less meaningful at the national level. The above-constructed variable, an output-based measure of academic research conducted at leading academic institutions, is considered to contain a substantial level of frontier academic knowledge.[9] It should be noted that although ARWU reports as many as 500 universities each year, they are distributed unevenly among countries, and only a small number of countries have a significant positive score from 2003 onwards.[10]

3.1.2. The measure of industrial R&D

Our measure of industrial R&D refers to the measure of total R&D capital stocks whose construction procedure is first initiated by Coe and Helpman (1995) and then widely followed by subsequent papers (e.g., Bayoumi *et al.*, 1999; Engelbrecht, 1997) in the R&D-based growth literature. In particular, data on nominal industrial R&D expenditure, after being collected from OECD Statistical Database, is deflated by an R&D price index to generate R&D expenditure. From this obtained real R&D data, we proceed to quantify domestic R&D capital stock measure for each of the OECD countries in the sample over the period of 2003-2017. In particular, R&D capital stock is calculated as the following: $SD_{it} = (1 - d)SD_{it-1} + RD_{it-1}$ where $d = 0.05$ denotes depreciation rate, and RD

[9] As an output-based measure, our frontier academic knowledge indicator is considered equivalent to the one used by Kerr (2010) that focuses on the top 1% of US patents. Because not all research output is patented, our measure is expected to cover the missing bit in the form of top academic publications.

[10] In 2003, among 500 universities listed, there were 219 universities from 23 countries in Europe, 193 universities from six countries in America, 83 universities from nine countries in the Asia Pacific and four universities from one country in the Middle East and Africa. In 2016, 210 universities were found from 25 countries in Europe, 165 in six countries in America, 114 in 10 countries in the Asia Pacific and 11 in four countries in the Middle East and Africa.

is real R&D expenditure. Here, the stock at the beginning of the period is computed according to $S_{i0} = \frac{RD_{i0}}{d+g}$ where g is the annual average growth rate from 2003 to 2017.

3.1.3. The measure of total factor productivity

We use TFP to capture technological progress as this is the factor that explains cross-country differences in GDP per capita over the last century (Hall and Jones, 1999). To calculate this variable, we collect data on value-added, gross capital formation and labor employment from the World Development Indicators Database (WDI) of the World Bank. From these data series, we compute capital stock from gross capital formation based on the perpetual inventory method (similar to what is used for computing the domestic R&D capital stock described above). After that, we calculate TFP for each country in the sample using the stochastic frontier method proposed by Battese and Coelli (1988, 1992) and Coelli *et al.* (1998).

3.1.4. Other variables

In the econometric framework that we discuss later in the paper, besides the main variables of interest, we also control for explanatory variables that vary with country and year that affect technological development. In doing so, we construct two variables: human capital stock and import-GDP ratio. While data for human capital is extracted from the Penn World Table (version 9.0), data for the import-GDP ratio is sourced from OECD Statistical Database.

3.1.5. Summary statistics

Table 1. Summary statistics

Country	TFP		SD		SA		HC		IM	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Australia	0.902	0.038	56,683.357	11,532.466	1,172.273	264.746	3.474	0.028	0.214	0.008
Austria	0.484	0.020	29,974.106	3,863.485	285.453	23.396	3.272	0.062	0.478	0.032
Belgium	0.427	0.018	26,862.907	2,923.868	452.040	29.311	3.093	0.030	0.749	0.059
Canada	1.044	0.044	109,856.032	17,100.211	1,557.780	64.556	3.640	0.051	0.325	0.011
Denmark	0.225	0.009	19,377.639	4,795.330	342.653	42.799	3.446	0.071	0.456	0.040
Finland	0.279	0.012	18,685.325	2,273.958	283.760	18.301	3.332	0.088	0.371	0.029
France	1.178	0.050	147,689.256	14,070.547	1,151.040	55.146	3.061	0.080	0.289	0.023
Germany	1.415	0.059	211,149.875	21,082.299	2,323.800	91.580	3.642	0.026	0.367	0.037
Ireland	1.000	0.000	7,495.037	1,738.551	143.887	18.907	3.030	0.078	0.821	0.121
Italy	1.180	0.050	126,174.331	4,365.508	1,072.933	86.424	2.987	0.091	0.261	0.018
Japan	1.847	0.078	351,281.159	6,280.423	1,669.647	391.142	3.489	0.059	0.151	0.028

Netherlands	0.714	0.030	62,412.644	6,942.336	911.447	59.188	3.273	0.060	0.638	0.071
Norway	0.018	0.001	17,725.985	2,742.938	220.913	22.031	3.549	0.076	0.292	0.021
Spain	1.263	0.053	62,611.058	9,058.504	529.700	96.618	2.809	0.083	0.294	0.020
Sweden	0.497	0.021	44,445.685	4,573.690	693.593	22.345	3.339	0.060	0.395	0.021
Switzerland	0.430	0.018	36,130.136	5,783.282	646.913	48.269	3.629	0.041	0.514	0.005
UK	1.202	0.051	123,930.722	16,843.016	2,957.460	87.442	3.681	0.063	0.292	0.018
US	1.823	0.077	722,711.410	93,532.603.	13,345.910	748.221	3.685	0.044	0.157	0.012

***Notes*:** TFP, SD, SA, HC and IM are TFP, industrial R&D, frontier academic research, human capital and import-GDP ratio, respectively.

In Table 1, we provide a summary of key data series for 18 OECD countries over the 2003-2017 period. It can be seen that, on average, TFP is highest in Japan, followed by that in the US and Germany. Meanwhile, Scandinavian countries have the most modest levels of TFP.

Between 2003-2017, industrial R&D capital stock increased substantially in all countries. This reflects large investments in R&D in the sample countries over the last few decades. The highest stock is recorded in the US, followed by Japan and Germany. By contrast, Ireland and Finland experienced the smallest accumulation of industrial R&D.

There is also a wide spectrum in frontier academic research capital stocks across the countries over the sample period. While the US, the UK, and Germany occupy top spots, Ireland and Norway are bottom countries in terms of this R&D stock. Other countries enjoyed a reasonable score for this item.

All countries scored rather well in terms of stock of human capital. The indices exhibit a somewhat homogenous pattern across countries. The US, the UK, and Germany enjoyed the highest scores, while Spain and Italy had the most modest ones. However, the gap between the two groups is not substantially large.

Finally, all countries were quite open to imports during 2003-2017. Imports as a share of GDP were recorded highest in Ireland and the Netherlands. On the opposite side, there were the lowest in the US and Japan.

3.2. The empirical model and estimation strategy

To test the indirect effect and total effect of frontier academic research on TFP, we follow Aiken and West's (1991) hierarchy procedure that includes four different steps as follows: (i) examining the effect of frontier academic research on TFP without considering industrial R&D; (ii) examining the effect of industrial R&D on TFP without including frontier academic research; (iii) examining the effects on TFP of both variables simultaneously; and (iv) examining the interaction effect of both variables on TFP.[11] This procedure enables the detection of a potential interaction effect of the two key predictors of TFP. We include the same control variables in these steps. In particular, we use the following equations, each of which corresponds to a single step above:

$$\log(TFP_{it}) = \alpha_i + \beta_1 \log(SA_{i,t-2}) + \delta X_{i,t-1} + \gamma_t + \varepsilon_{i,t}, \quad (1)$$

$$\log(TFP_{it}) = \alpha_i + \alpha_1 \log(SD_{i,t-1}) + \delta X_{i,t-1} + \gamma_t + \varepsilon_{i,t}, \quad (2)$$

$$\log(TFP_{it}) = \alpha_i + \alpha_2 \log(SD_{i,t-1}) + \beta_2 \log(SA_{i,t-1}) + \delta X_{i,t-1} + \gamma_t + \varepsilon_{i,t}, \quad (3)$$

$$\log(TFP_{it}) = \alpha_i + \alpha_3 \log(SD_{i,t-1}) + \beta_3 \log(SA_{i,t-2}) + \mu \log(SD_{i,t-1}) * \log(SA_{i,t-2}) + \delta X_{i,t-1} + \gamma_t + \varepsilon_{i,t}. \quad (4)$$

In these formulations, TFP is the TFP level, SD is the measure of industrial R&D capital stock, SA is the measure of frontier academic research capital stock, X is the vector of control variables that affect TFP, such as stock of human capital and import as a share of GDP, α_i is a country-specific fixed effect that picks up effects of time-invariant factors on technological progress such as institutions, γ_t is a time-specific fixed effect that absorbs time-varying characteristics, such as macroeconomic shocks, and ε is an error term.[12] Note that in running these regressions, while we lag all independent variables by one year, we lag $\log(SA)$ by two years. This is to capture the notion that any change in these variables takes time to materialize its effect on TFP and the effect of academic

[11] In this section, for a succinct presentation, we discuss the empirical model only. A theoretical model that lays the foundation for the regression equations below can be found in Appendix A.

[12] Other factors that may affect TFP include infrastructure, geography and institutions. However, these factors generally do not vary much with time and, therefore, can be picked up by the fixed effects.

research may take even longer than that of industrial R&D. In addition, this helps mitigate any potential reverse causality between these variables and TFP. The only exception is Equation (3) where we lag $\log(SA)$ by only one year to capture the direct effect of frontier academic research on TFP. A simplified characterization of the causation chain is as follows:[13]

- The indirect effect: frontier academic research in year $t-2$ has an effect on industrial R&D in year $t-1$ which then affects TFP in year t. This means that industrial R&D acts as an absorptive factor to adapt frontier academic research to particular needs of industrial firms and transform it into process or product innovations that lead to productivity improvement. This process is linked to complex academic research that is difficult to be implemented without making its way through the specialized R&D section of an industrial firm.
- The direct effect: frontier academic research in year $t-1$ directly affects TFP in year t. This effect is linked to frontier academic research that is easier to be adapted and implemented by firms.

To test the indirect effect of frontier academic research on TFP and whether industrial R&D is an effective mediating factor, we follow Baron and Kenny's (1986) four-step procedure, of which three steps are as presented in Equations (1) - (3). Equation (1) estimates the total effect of frontier academic research that measures the degree to which TFP (i.e., the dependent variable) changes in response to a one-unit increase in the frontier academic knowledge (i.e., the independent variable), given that industrial R&D (i.e., the mediation variable) is unchanged. While Equation (2) tests the significance of industrial R&D on TFP, Equation (3) examines the direct effect of frontier academic research on TFP (in the presence of the direct effect of industrial R&D). In the last step, we conduct a regression analysis to see how frontier academic knowledge predicts industrial R&D:

[13] One may argue that innovations and technological progress take place continuously. As such, while this characterization in discrete-time aims to provide an improved understanding of the causation chain, it is indeed a simplified version of the reality. We are grateful to an anonymous referee for a useful suggestion on this causation chain characterization.

$$\log(SD_{it}) = \alpha_i + \beta_4 \log(SA_{i,t-1}) + \gamma_t + \varepsilon_{i,t}. \tag{5}$$

An important goal of the mediation analysis is to compute the indirect effect of frontier academic knowledge on TFP and check if it is statistically significant. Sobel (1982) suggests the following computation for the indirect effect:

$$\beta_{indirect} = \alpha_2 * \beta_4. \tag{6}$$

Once this indirect effect is calculated, it needs to be tested because so far, the significance of the indirect pathway that frontier academic knowledge affects TFP through the compound pathway from frontier academic research to industrial R&D and from industrial R&D to TFP has not been tested yet. To that end, we conduct the test put forward by Sobel (1982), whose test statistic is calculated as follows:

$$t = \frac{\alpha_2 * \beta_4}{\sqrt{\alpha_2^2 * Var(\beta_4) + \beta_4^2 * Var(\alpha_2)}} \tag{7}$$

where $Var(\alpha_2)$ and $Var(\beta_4)$ are the variance of α_1 and β_3, respectively. This t-statistic follows a normal distribution.

4. Empirical results

4.1. The technological impact of frontier academic knowledge

Table 2 reports results on the effect of frontier academic research on TFP obtained from estimating Equations (1) - (5) using the OLS estimation method. All equations include unreported country- and time-specific effects as well as the measure of human capital and import-GDP ratio as control variables.[14]

The results show that that the coefficient estimate of $\log(SA)$ is positive and significant at a 1% level when it is included in column (2.1). This preliminary finding appears to support the notion that

[14] Other factors that may affect TFP include infrastructure, geography, climate and institutions. However, given that these factors vary little with time, they can be subsumed into the fixed effects.

frontier academic knowledge contributes significantly and positively to innovation improvement. This also means that frontier academic research exerts a *positive total effect* on technological progress. This result is in line with Eid (2012) and Le and Tang (2015) despite using a different measure of academic research. Therefore, ***H1 is accepted.***

Column (2.2) reveals that industrial R&D has a strong predicting power of future changes in technology as evidenced by a positive and significant coefficient (at 1% level of significance) of $\log(SD)$. This result is consistent with the findings in Coe and Helpman (1995) and many other papers in the growth literature that industrial R&D is an important source of technological advancement.

In column (2.3), when both frontier academic research (lagged by only one year) and industrial R&D are included, the coefficient of frontier academic research becomes negative and significant at 5% level, while that of industrial R&D is still positive and highly significant at 1% level. This means that, in the presence of industrial R&D, the *direct effect* of frontier academic research on TFP is negative. This is generally in line with Gittelman and Kogut (2003), who report a negative relationship between important scientific papers and patented innovations,a proxy of technological progress, in biotechnology. This interesting result can be explained by the distinctive feature of frontier academic research. According to Dasgupta and David (1994), in the research race, academic science does not normally pay big rewards to the runners-up because among the discoveries (or inventions) made by rivals in parallel research, only the one published first is recognized. As society attaches little added value to the other competing discoveries, investments made in these research projects are wasted. This is because these investments could have been made in productive academic activity, such as education and training, instead. In the same vein, Aguinis *et al.* (2020) argue that excessive focus on top-levelled publications in academic research may incentivize talented researchers to conduct research for the sake of publication rather than the one that makes real economic contributions. Therefore, in general, while frontier academic research creates knowledge that can be adapted and implemented by firms, it may also entail some hidden costs to society. When such the benefit is outweighed by the associated wastage, the net direct effect of frontier academic research will be negative.

In column (2.4), both types of R&D yield positive and significant coefficients. While the coefficient of their interaction term is also significant, it has a negative sign. These results suggest that frontier academic knowledge does exert an important effect on TFP although this effect is faded by the presence of industrial R&D. Although this study started with the interest in the mediating effect of industrial R&D on the frontier academic research – TFP nexus, the result in this column indicates a potential form of moderating effect of industrial R&D as well. To investigate this issue further, we calculate the marginal (direct) effect of frontier academic research on TFP as follows:

$$\frac{\partial \log(TFP)}{\partial \log(SA)} = 0.185 - 0.017 * \log(SD) \quad (8)$$

Clearly, the net (direct) effect of frontier academic research on TFP is conditional on industrial R&D. Specifically, there exists a threshold of industrial R&D (i.e., $\log(SD) = 10.882$ or $SD = 53{,}209.913$) below which frontier academic research effectively and positively induces TFP. Conversely, countries with a high level of industrial R&D would see a negative net (direct) effect of frontier academic research on TFP due to the moderation of industrial R&D on frontier academic research.[15] A possible explanation for this negative direct effect is that countries with a high level of industrial R&D tend to put more emphasis on industrial R&D than frontier academic research in advancing their aggregate productivity. This may be because the relative abundance of industrial R&D in these countries renders this type of R&D with some relatively cost-effective advantage in inducing TFP, compared to its frontier academic research counterpart. As such, frontier academic research might be highly influenced by industrial R&D (e.g. through industrial linkage grants). In that respect, instead of being totally published in open science, frontier academic research may contain a project pre-committed to industrial R&D in which findings are proprietary and not to be

[15] A quick glance at Table 1 indicates that countries having industrial R&D above this threshold include Australia, Canada, France, Germany, Italy, Japan, the Netherlands, Spain, the UK and the US.

disclosed publicly. Secretiveness resulting from the intertwining between frontier academic research and industrial R&D, even in the form of partial disclosure, omission of information required for replication or delayed circulation of research results, will generate another source of wastage of social resources (Dasgupta and David, 1994). This result also helps explain the negative (direct) effect of frontier academic research obtained in column (2.3). Most countries in the sample have industrial R&D above the threshold level, leading to an overall negative (direct) effect of frontier academic research for the whole sample result.

Next, we check if industrial R&D carries any effect of frontier academic research. The estimate in column (2.5) indicates that frontier academic knowledge strongly influences industrial R&D. The coefficient of $\log(SA)$ is positive and statistically significant at 1% level. This means that industrial R&D also mediates the relationship between frontier academic research and TFP. Hence, ***H2 is accepted***.

Table 2. OLS regression results (two-way fixed effects, 18 countries, 2003-2017)

	Dependent variable: $\log(TFP_t)$				Dependent variable: $\log(SD_{t-1})$
	(2.1)	(2.2)	(2.3)	(2.4)	(2.5)
$\log(SD_{t-1})$		0.056^{***}	0.065^{***}	0.165^{***}	
		(0.011)	(0.009)	(0.029)	
$\log(SA_{t-1})$			-0.010^{**}		
			(0.004)		
$\log(SA_{t-2})$	0.015^{***}			0.185^{***}	0.363^{***}
	(0.006)			(0.041)	(0.022)
$\log(SD_{t-1}) * \log(SA_{t-2})$				-0.017^{***}	
				(0.004)	
$\log(HC_{t-1})$	0.048^{**}	0.042^{***}	0.047^{***}	0.061^{***}	
	(0.019)	(0.009)	(0.009)	(0.010)	
IM_{t-1}	0.002^{***}	0.001^{***}	0.001^{***}	0.001^{***}	
	(0.000)	(0.000)	(0.000)	(0.000)	
R^2	0.965	0.970	0.999	0.975	0.999
$Adj. R^2$	0.959	0.965	0.999	0.971	0.998
Observations	234	252	252	234	270

***Notes*:** $\log(X)$ is log of X; TFP, SD, SA, HC and IM are TFP, industrial R&D, frontier academic research, human capital and import-GDP ratio. Robust standard errors are in parentheses. *, **, *** indicate parameters that are significant at 10%, 5%, and 1% levels of significance, respectively. All regressions include unreported country-specific and time-specific constants.

Having obtained all regression results, we now move on to calculate the indirect effect. From Table 2, we get $\alpha_2 = 0.065$ and $\beta_4 = 0.363$. The indirect effect calculated based on Sobel's (1982) method, described in Equation (7), gives $\beta_{indirect} = 0.065 * 0.363 = 0.024$. For the computation of Sobel's (1982) test statistic, we have $Var(\alpha_2) = 0.009^2$ and $Var(\beta_4) = 0.022^2$. Inserting these values together with $\alpha_2 = 0.065$ and $\beta_4 = 0.363$ into Equation (7) gives $t = 6.616$. Because t has a normal distribution, it is significant at a 1% level of significance.

In short, the obtained results are interesting. On the one hand, industrial R&D weakens the direct effect of frontier academic research on TFP. On the other hand, it strengthens the indirect effect of the latter on TFP. A possible explanation for these results is that countries with a high level of industrial R&D are perhaps less reliant on frontier academic research to innovate and achieve productivity increments.

Regarding the control variables, we find that the estimated coefficients for $\log(HC)$ and IM are both positive and highly significant throughout. These results are in line with existing studies in the literature confirming the role of human capital and imports in facilitating a technological change of a country (Coe and Helpman, 1997; Engelbrecht, 1997).

4.2. Long-run relationships

In this subsection, we check if the relationships among our variables of interest hold in the long run. To that aim, we apply the panel cointegration method for the variables. The first criterion for the conduct of this method is to have non-stationary variables. At a 10% level of significance, we perform unit root tests, first proposed by Hadri (2000) (with the null hypothesis of stationarity on the variable) then by Im *et al.* (2003) (with the null hypothesis positing the existence of an individual unit root process) on the variables. Obtained results on panel unit root tests in Table 3 reveal the overall non-stationarity for most variables. The only exception is the import-GDP ratio, IM, which is non-stationary under Hadri's (2000) test but stationary under Im *et al.*'s (2003) test. In conclusion, we are inclined towards using the outcome from Hadri's test as with the purpose of proving a certain variable to be non-stationary, its null hypothesis seems more appropriate.

Table 3. Panel unit root tests (at 10% level of significance, 18 countries, 2003-2017)

	Hadri's (2000) test		Im *et al.*'s (2003) test		
Variable	Statistics	Implication	Statistics	Implication	Decision
$\log(TFP)$	10.130 (0.000)	$I(1)$	0.677 (0.751)	$I(1)$	$I(1)$
$\log(SD)$	12.464 (0.000)	$I(1)$	1.607 (0.946)	$I(1)$	$I(1)$
$\log(SA)$	7.599 (0.000)	$I(1)$	3.903 (1.000)	$I(1)$	$I(1)$
$\log(HC)$	12.324 (0.000)	$I(1)$	2.037 (0.979)	$I(1)$	$I(1)$
IM	10.594 (0.000)	$I(1)$	-2.798 (0.002)	$I(0)$	$I(1)$

Notes**:** $\log(X)$ is log of X; $TFP, SD, SA,$ HC and IM are TFP, industrial R&D capital, frontier academic research, human capital and import-GDP ratio, respectively. p-values are in parentheses. $I(1)$ indicates the existence of a unit root.

We next examine if the variables exhibit any cointegrating relationship by conducting two-panel cointegration tests (with the null hypothesis of no cointegrating relationship among variables) suggested by Pedroni (1999) at 10% level of significance. Obtained results in Table 4 generally show the existence of a cointegrating, hence, a long-term relationship between variables of interest. This means that associated regressions involved in these trended variables are free from being spurious and can be estimated with either pool or group mean estimation technique. This also means that our variables exhibit important long-run relationships and all panel least squares (OLS) regressions conducted in Subsection 4.1 reveal these relationships.

Table 4. Panel cointegration tests (at 10% level of significance, 18 countries, 2003-2017)

Variables	Panel ADF-statistics	Group ADF-statistics	Decision
$\log(TFP)$, $\log(SA)$, $\log(HC)$, IM	-1.727 (0.042)	0.209 (0.583)	CI

$\log(TFP)$, $\log(SD)$, $\log(HC)$, IM	-1.233 (0.109)	-1.478 (0.070)	CI
$\log(TFP)$, $\log(SA)$, $\log(SD)$, $\log(HC)$, IM	-4.008 (0.000)	-2.147 (0.016)	CI

***Notes*:** $\log(X)$ is log of X; $TFP, SD, SA,$ HC and IM are TFP, industrial R&D, frontier academic research, human capital and import-GDP ratio, respectively. p-values are in parentheses. CI indicates cointegrated.

Although the OLS results are interesting, they may be subject to a second-order asymptotic bias, as discussed by Kao *et al.* (1999) and Tsionas (2019). This problem arises when the associated standard errors are not consistently estimated due to the potential endogeneity of the regressors, even though there is cointegration (Tsionas, 2019). In this context, there is some concern over the potential reverse causality between the R&D variables and TFP.[16] To avoid this potential problem, we re-estimate Equations (1) - (5) using the dynamic OLS (DOLS) technique proposed by Kao and Chiang (2000) to take advantage of its superior small sample properties and report the results in Table 5. This technique makes an important adjustment to this bias by using the dynamic of regressors, such as leads and lags of the differenced regressors, as an internal instrument (Tsionas, 2019).[17] In running these regressions, we choose one lead and one lag for the cointegrating regressors due to our short-time horizon.

Table 5. DOLS regression results (two-way fixed effects, 18 countries, 2003-2017)

	Dependent variable: $\log(TFP_t)$				Dependent variable: $\log(SD_{t-1})$
	(5.1)	(5.2)	(5.3)	(5.4)	(5.5)
$\log(SD_{t-1})$		0.031^{***} (0.009)	0.050^{***} (0.008)	0.139^{***} (0.041)	
$\log(SA_{t-1})$			-0.017^{***} (0.004)		
$\log(SA_{t-2})$	0.012^{**} (0.005)			0.137^{***} (0.048)	0.409^{***} (0.030)
$\log(SD_{t-1}) * \log(SA_{t-2})$				-0.014^{***} (0.004)	
$\log(HC_{t-1})$	0.038^{**} (0.017)	0.030^{*} (0.015)	0.063^{***} (0.015)	0.061^{***} (0.018)	
IM_{t-1}	0.002^{***} (0.001)	0.002^{***} (0.000)	0.002^{***} (0.000)	0.001^{***} (0.000)	
R^2	0.969	0.977	0.999	0.979	0.999

[16] Although we lag these variables by one to two years, this may not fully address the issue of potential endogeneity.

[17] Pedroni (1999) proposes an equivalent method known as fully modified OLS (FMOLS). Unlike DOLS, FMOLS makes an adjustment to the bias via nonparametric estimates of autocovariances (Tsionas, 2019). We choose the DOLS instead of FMOLS method for our regressions due to its superior small sample properties, as discussed in Kao and Chiang (2000).

$Adj. R^2$	0.961	0.971	0.999	0.972	0.999
Observations	198	216	216	180	216

***Notes*:** $\log(X)$ is log of X; $TFP, SD, SA,$ HC and IM are TFP, industrial R&D, frontier academic research, human capital and import-GDP ratio, respectively. Robust standard errors are in parentheses. *, **, *** indicate parameters that are significant at 10%, 5%, and 1% levels of significance, respectively. All regressions include unreported country-specific and time-specific constants as well as one lead and one lag for the cointegrating regressors.

Table 5 presents results for the same regressions in Table 2 but obtained by using DOLS method. It can be seen that the obtained coefficient of $\log(SD)$ is generally the same as OLS results in terms of sign and significance across regressions. However, its magnitude is larger under DOLS method. The estimated coefficient of $\log(SA)$ qualitatively stays the same as in the OLS regressions. The interaction term between $\log(SD)$ and $\log(SA)$ remains negative and highly significant (at 1% level), as shown in column (5.4). The results in column (5.3) indicate that, on average (for the whole sample), the direct effect of frontier academic research on TFP (in presence of industrial R&D) is negative. Column (5.4) shows the threshold level of industrial R&D above which the direct effect of frontier academic research on TFP becomes negative (i.e., $\log(SD) = 9.786$ or $SD = 17.783$. This threshold level technically divides the sample countries into two groups: those having a positive effect (Ireland and Norway) versus those having a negative effect (all other sample countries). Since most countries have a negative effect, the sample's average result in (5.3) is negative. In (5.5), frontier academic knowledge continues to strongly predict industrial R&D. As for human capital and import as a share of GDP, their coefficients are all positive and highly significant across regressions. Overall, the obtained results indicate that frontier academic research exerts a real effect in promoting technological development in the economy. Notably, a large portion of this impact is funneled via industrial R&D investment (i.e., the indirect effect). This finding is generally in line with Cohen and Levinthal (1989) and Aghion and Jaravel (2015) that confirm the role of industrial R&D in enhancing firms' ability to assimilate and exploit existing information. However, industrial R&D seems to weaken the direct effect of frontier academic research on technological progress.

4.3. Sensitivity analysis

It may be argued that among the indicators used to construct the frontier academic knowledge, the one capturing academic publications may be the key factor affecting technological progress. To accommodate this, we consider the following variable:

$$Pub_{jt} = \sum_k Pub_{kt} \;. \tag{9}$$

In addition, we consider a variation of this variable by adding scores on publications in *Nature* and *Science*. These are regarded as top journals in science and engineering, the probably most relevant fields for industrial production. The variant indicator reads as follows:

$$NSPub_{jt} = \sum_k (NS_{kt} + Pub_{kt}). \tag{11}$$

In Tables 6 and 7, we report our DOLS results for regressions involved academic publication scores. The results are similar to what was included in Table 5. Academic research in terms of publications in indexed journals seems to exert some impact on technological progress. While the direct impact is weakened by industrial R&D, its indirect impact on TFP is strengthened by this factor. Overall, there is still a net positive impact on TFP as evidenced by positive and significant coefficients of $\log(Pub)$ in (6.1) and $\log(NSPub)$ in (7.1), respectively.

Table 6. DOLS regression results (two-way fixed effects, 18 countries, 2003-2017)

	Dependent variable: $\log(TFP_t)$				Dependent variable: $\log(SD_{t-1})$
	(6.1)	(6.2)	(6.3)	(6.4)	(6.5)
$\log(SD_{t-1})$		0.031***	0.057***	0.120***	
		(0.009)	(0.010)	(0.038)	
$\log(Pub_{t-1})$			-0.020***		
			(0.003)		
$\log(Pub_{t-2})$	0.008**			0.126**	0.363***
	(0.004)			(0.051)	(0.019)
$\log(SD_{t-1}) * \log(Pub_{t-2})$				-0.012***	
				(0.004)	
$\log(HC_{t-1})$	0.037**	0.030*	0.068***	0.068***	
	(0.017)	(0.015)	(0.017)	(0.019)	
IM_{t-1}	0.002***	0.002***	0.002***	0.001***	
	(0.001)	(0.000)	(0.000)	(0.000)	
R^2	0.968	0.977	0.999	0.999	0.999
$Adj.R^2$	0.960	0.971	0.999	0.999	0.999
Observations	198	216	216	180	216

Notes: $\log(X)$ is log of X; TFP, Pub, HC and IM are TFP, publication score, human capital and import-GDP ratio, respectively. Robust standard errors are in parentheses. *, **, *** indicate parameters that are significant at 10%, 5%, and 1% levels of significance, respectively. All regressions include unreported country-specific and time-specific constants. DOLS regressions include one lead and one lag for the cointegrating regressors (not reported).

Table 7. DOLS regression results (two-way fixed effects, 18 countries, 2003-2017)

	Dependent variable: $\log(TFP_t)$				Dependent variable: $\log(SD_{t-1})$
	(7.1)	(7.2)	(7.3)	(7.4)	(7.5)
$\log(SD_{t-1})$		0.031^{***}	0.048^{***}	0.118^{***}	
		(0.009)	(0.009)	(0.035)	
$\log(NSPub_{t-1})$			-0.017^{***}		
			(0.004)		
$\log(NSPub_{t-2})$	0.008^{*}			0.137^{***}	0.342^{***}
	(0.004)			(0.047)	(0.020)
$\log(SD_{t-1}) * \log(NSPub_{t-2})$				-0.013^{***}	
				(0.004)	
$\log(HC_{t-1})$	0.020	0.030^{*}	0.043^{**}	0.034^{*}	
	(0.017)	(0.015)	(0.021)	(0.020)	
IM_{t-1}	0.002^{***}	0.002^{***}	0.002^{***}	0.001^{***}	
	(0.001)	(0.000)	(0.000)	(0.000)	
R^2	0.999	0.977	0.999	0.999	0.999
$Adj. R^2$	0.999	0.971	0.999	0.999	0.998
Observations	198	216	216	180	216

***Notes*:** $\log(X)$ is log of X; TFP, $STEM$, HC and IM are TFP, score on publications in STEM, human capital and import-GDP ratio, respectively. Robust standard errors are in parentheses. *, **, *** indicate parameters that are significant at 10%, 5%, and 1% levels of significance, respectively. All regressions include unreported country-specific and time-specific constants. DOLS regressions include one lead and one lag for the cointegrating regressors (not reported).

So far, we have been using TFP data calculated based on the stochastic frontier method as per Battese and Coelli (1988, 1992) for our regressions. However, as a large number of studies in the R&D-based growth literature calculate TFP based on the growth accounting method in which TFP is treated as the Solow residuals, it is important to see whether our results still hold when TFP is calculated this way. To that end, we additionally run regressions in which the dependent variable is TFP computed based on the growth accounting method. We report obtained results in Table 8.

As shown in Table 8, results for $\log(SD)$ and $\log(SA)$, and their interaction term, are generally the same in terms of sign and significance except for regression (8.3), where both coefficients are insignificant. While human capital is not at all significant, import-GDP ratio is only significant at

10% level. The lower R^2 indicates lower goodness of fit when this TFP data series is used. Given this poor performance of data calculated based on the growth accounting method, the stochastic frontier method proposed by Battese and Coelli (1988, 1992) is clearly preferable in calculating TFP.

Table 8. DOLS regression results using TFP data from growth accounting method (two-way fixed effects, 18 countries, 2003-2017)

	Dependent variable: $\log(TFP_t)$				Dependent variable: $\log(SD_{t-1})$
	(8.1)	(8.2)	(8.3)	(8.4)	(8.5)
$\log(SD_{t-1})$		0.041**	0.010	0.147**	
		(0.016)	(0.033)	(0.066)	
$\log(SA_{t-1})$			0.025		
			(0.022)		
$\log(SA_{t-2})$	0.042***			0.197***	0.409***
	(0.012)			(0.065)	(0.030)
$\log(SD_{t-1}) * \log(SA_{t-2})$				-0.016***	
				(0.006)	
$\log(HC_{t-1})$	-0.050	0.012	-0.047	-0.040	
	(0.056)	(0.027)	(0.041)	(0.063)	
IM_{t-1}	0.001*	0.001*	0.001*	0.000	
	(0.000)	(0.000)	(0.000)	(0.001)	
R^2	0.649	0.665	0.674	0.660	0.999
$Adj. R^2$	0.569	0.589	0.590	0.542	0.999
Observations	216	216	216	180	216

***Notes*:** $\log(X)$ is log of X; TFP, SD, SA, HC and IM are TFP, industrial R&D, frontier academic research, human capital and import-GDP ratio, respectively. Robust standard errors are in parentheses. *, **, *** indicate parameters that are significant at 10%, 5%, and 1% levels of significance, respectively. All regressions include unreported country-specific and time-specific constants as well as one lead and one lag for the cointegrating regressors.

Finally, for further robustness check, we employ ARWU scores behind field rankings in science, technology, engineering and mathematics (available over 2007-2016) and THE data (available over 2011-2017) to estimate Equations (1), (3) - (5). The obtained results presented in Tables B1 and B2 in Appendix B show a somehow robust and significant effect of frontier academic research on technological progress. Meanwhile, the coefficient of industrial R&D is mostly insignificant, although it is still positive. We treat these results with a little caution because the short time horizons (2007-2016 or 2011-2017) could hardly capture in full the long-run relationship between the interested variables.

In summary, the obtained results converge to the point that frontier academic knowledge performance has an important implication for technological improvement. Notably, the impact largely goes through industrial R&D investment. These results are robust across alternative proxies for frontier academic knowledge and different estimation methods and specifications (including different lead and lag structures).

5. Discussion and conclusions

This paper provides rigorous empirical evidence that R&D investment is a major factor explaining TFP differences across countries. While the role of industrial R&D has been well established in the literature, the result that frontier academic knowledge, generated by top universities worldwide, exerts a significant effect on technological improvement is new. This result is distinct from, but also complementary to, a pioneering work that advocates the role of academic research on industrial innovation at the micro-level (e.g., Acs *et al.*,1992; Jaffe, 1989; Mansfield, 1991, 1998) as well as a few recent studies that examine the economic impact of academic research at the macro-level (i.e., Eid, 2012; Le and Tang, 2015). Our finding highlights the importance of academic research investment, which benefits the whole economy, not just some individual industries, as previously identified by micro-level studies. In that respect, it challenges the view that underestimates the real contributions of academic research, especially of the one at the frontier level. Even if frontier academic research is driven by academic fame, its real impact on a country's technological progress cannot be refuted.

More importantly, the finding that the effect of academic research on TFP is largely transferred through industrial R&D investment is interesting and novel. This mediating channel has been omitted in the extant literature despite a significant amount of research examining the total effect of academic research and industrial R&D on TFP at both macro and micro levels. This finding implies that although the public good produced in the academic research process is beneficial, its benefit cannot be fully utilized without a reciprocal investment in industrial R&D. More importantly, our findings show that industrial R&D enhances the indirect effect of frontier academic research on TFP, but it, at the same time, diminishes the direct effect of frontier academic research on TFP. These findings reflect the creative destruction of academic knowledge: once academic knowledge is fully transferred to the industry, that knowledge loses its attractiveness in production and requires improvement.

Our theoretical framework is distinct from, but also complementary to, a few recent studies that consider the economic impact of academic research at the macro level. In particular, using the data of 17 high-income OECD countries over the period of 1981-2006, Eid (2012) finds the significant and positive effect of academic research on productivity growth. He employs gross R&D expenditure to proxy for academic research and the average growth of real output per worker to the proxy for productivity growth. Le and Tang (2015), based on a dataset spanning 28 OECD and emerging countries over the 1991–2005 period, report that academic research exerts a larger growth effect on high-tech manufacturing output than its industry and government counterparts. The authors employ a supercomputer calculation capacity to proxy for academic research. However, because these papers only consider the total effect of academic research on technological progress, the important indirect effect of this factor that is transmitted through industrial R&D has been left unexamined.

Moreover, unlike the extant literature that relies heavily on R&D expenditure or patent counts/citations to proxy for academic research investment, we propose a new output-based measure computed from research scores of Top 500 universities in the Academic Rankings of World Universities. In particular, research scores of all listed universities will be summed up to give their national research scores. The rationale for the use of this indicator is that because knowledge is tacit and not easy to be measured, it needs to be captured via academic performance. Accordingly, universities' research capacity reveals the most of this knowledge pool. As an input-based measure, academic R&D expenditure may be too broad to capture the true nature of innovation as the process from R&D investment to innovation outputs is full of uncertainties; not all research projects are successful. Calculated based on a monetary value, this measure is also subject to measurement errors resulting from monetary conversion across different national currencies or time periods. Our research score measure helps mitigate these errors. Meanwhile, the main drawback of using patent counts/citations is that these data miss out on an important part of academic research in the form of academic publications. Also, while patents are largely private properties, academic publications are generally considered a public good.

In addition to theoretical contributions, this study offers fruitful implications to practice. For policymakers, we suggest that governments should fund scientific research to achieve sustainable growth. In working out their funding strategies, they should balance between funding to stimulate innovations in the higher education sector and that in the industry. There should also be funding schemes that closely link frontier academic research direction with the demand to solve emerging issues of the industry and society. For researchers at universities and firms, we strongly recommend them to be proactive in collaborations for research, technological transfer and diffusion of academic knowledge as these channels are proved to be beneficial to research outputs at both types of organizations.

Our paper opens several important avenues for future research. One dimension would be to use data from other university ranking league tables, such as those by THE or QS when the data on research scores is available in longer time series to further test the robustness of the measure of frontier academic research. Another direction is to include institutional variables in the regressions, given that these factors have increasingly been confirmed as deep determinants of economic growth within this growth literature. All these suggest an exciting research agenda in the future.

Acknowledgement:

The authors would like to thank three anonymous reviewers for their constructive comments. We also greatly appreciate the Editor of this journal, Professor Stelvia Matos, for the efficient handling of our submission. The usual disclaimers apply.

Funding declaration:

This research is funded Vietnam National Foundation for Science and Technology Development (NAFOSTED) under grant number 502.01-2019.01.

Appendix A

The theoretical model

We develop the following theoretical model to explain the roles of academic and industrial research in advancing technological progress. This model is built based on seminal works in endogenous growth literature such as Romer (1990), Grossman and Helpman (1991) and Aghion and Howitt (1992). We then link this theoretical model to the empirical model in Subsection 3.2 in the main text.

Consider a country that consists of a large number of final goods producers whose aggregate production function takes the following form:

$$Y_t = AK_t^{\beta}\Omega_t^{\alpha}L_t^{1-\alpha-\beta}, 0 < \alpha, \beta, \alpha+\beta < 1, \tag{A1}$$

where Y_t, K_t and L_t denote the output level, stock of physical capital and labor employment at time t respectively. While A is a scale factor, Ω_t is a continuum of intermediate products such that:

$$\Omega_t = \left[\int_0^{N_t} \lambda_{vt} x_{vt}^{\alpha} dv\right]^{\frac{1}{\alpha}}. \tag{A2}$$

In this equation, N_t is the range of intermediate inputs and x_{vt} is the amount of intermediate product of the latest vintage v whose quality grade is λ_{vt}. Each intermediate good is produced by a monopolistic firm until being replaced by an innovator with the successive vintage of the product (i.e. as a result of the creative destruction process). We normalize the production cost of each intermediate good to 1 for simplicity. We denote the monopoly price that each intermediate firm charges final good producers on its product as P_{vt}. Using (A1) and (A2), we work out the optimality condition following which the price of an intermediate product is equal to its marginal product:

$$\frac{\partial Y_t}{\partial x_{vt}} = AK_t^{\beta}L_t^{1-\alpha-\beta}\alpha\lambda_{vt}x_{vt}^{\alpha-1} = P_{vt}. \tag{A3}$$

Hence, demand for the intermediate good v is:

$$x_{vt} = \left(\frac{AK_t^{\beta}L_t^{1-\alpha-\beta}\alpha\lambda_{vt}}{P_{vt}}\right)^{\frac{1}{1-\alpha}}. \tag{A4}$$

Assuming that each intermediate good producer incurs a fixed set-up cost μ, its lifetime profit is:

$$\pi_{vt} = -\mu + \int_t^{\infty}(P_{vt} - 1)\, x_{vt}e^{-r(s-t)}ds. \tag{A5}$$

Here, $(P_{vt} - 1)x_{vt}$ is the instantaneous profit flow and r is the instantaneous interest rate at date s. The profit maximization problem of the representative intermediate firm at each date is:

$$Max_{P_{vt}}(P_{vt} - 1).\left(\frac{AK_t^{\beta}L_t^{1-\alpha-\beta}\alpha\lambda_{vt}}{P_{vt}}\right)^{\frac{1}{1-\alpha}}. \tag{A6}$$

This maximization problem delivers:

$$P_{vt} = \frac{1}{\alpha}. \tag{A7}$$

With a note that production cost is equal to 1, the monopoly price charged on the intermediate product is a mark-up over the marginal cost. (A7) and (A4) together determine the total demand for intermediate good v:

$$x_{vt} = \left(AK_t^{\beta} L_t^{1-\alpha-\beta} \alpha^2 \lambda_{vt}\right)^{\frac{1}{1-\alpha}}. \tag{A8}$$

This implies that demand is higher for products of higher quality. Substituting this result into the final goods production function in (A1) yields:

$$Y_t = \hat{A} \Lambda_t K_t^{\varphi} L_t^{1-\varphi}, \tag{A9}$$

where $\hat{A} = A^{\frac{1}{1-\alpha}} \alpha^{\frac{2\alpha}{1-\alpha}}$, $\varphi = \frac{\beta}{1-\alpha}$, and $\Lambda_t = \int_0^{N_t} \lambda_{vt}^{\frac{1}{1-\alpha}} dv$ representing the country's aggregate technology index. The development of this index includes both the introduction of new intermediate goods (increases in N_t) and quality enhancement (increases in λ_{vt}). Applying the growth accounting method (as per Solow, 1957) to define total factor productivity (TFP) as $TFP_t = \frac{Y_t}{K_t^{\varphi} L_t^{1-\varphi}}$, we have:

$$\log(TFP_t) = \log(\hat{A}) + \log(\Lambda_t). \tag{A10}$$

Note that in this paper we use TFP to capture the country's technological advancement. This is because TFP is the key factor that accounts for GDP per capita differences across countries over the last century (Caselli, 2005; Hall and Jones, 1999).

Equation (A10) implies that productivity is positively related to the range and quality of the intermediate products used. With research collaboration between universities and industrial firms, Λ_t essentially include both academic and industrial technological knowledge, which can be employed for a country's production. Denote industrial technological knowledge as SD_t and academic technological knowledge as SA_t then (A10) is equivalent to:

$$\log(TFP_t) = \log(\hat{A}) + \alpha_1 \log(SD_t) + \alpha_2 \log(SA_t) + \alpha_3 \log(SD_t) * \log(SA_t). \tag{A11}$$

It can be seen that this equation is similar to Equation (4) in Subsection 3.2 in the main text with an addition of control variables, fixed effects and an error term. In the same manner, if we either drop $\log(SD_t)$, $\log(SA_t)$ or their interaction term $\log(SD_t) * \log(SA_t)$, we will obtain Equations (1) - (3) in the main text.

Appendix B

Robustness checks using other datasets

Table B1 reports results on the impact of frontier academic research on TFP using data gathered from the field rankings published by ARWU. Because ARWU only publishes scores associated with the rankings during 2007-2016, our sample is shortened accordingly. To capture national frontier academic research for each country, we create an indicator named $STEM$, which is equal to the sum of scores on two different fields: Natural Sciences and Mathematics and Engineering/Technology and Computer Sciences. All regressions include unreported country- and time-specific effects as well as one lead and one lag for the cointegrating regressors, with human capital stock and import-GDP ratio as control variables. It can be seen that while the coefficient estimate for $STEM$ is statistically significant, that for industrial R&D is insignificant across the regressions. However, $STEM$ negatively affects SD in column (B1.4). While the coefficient of human capital is always insignificant, that of import-GDP ratio is significant in columns (B1.1) and (B1.2) but insignificant in (B1.3). This may be because the time span is not sufficiently long to display any stable long-run relationship between the interested variables.

Table B1. DOLS regression results using ARWU field rankings data (two-way fixed effects, 18 countries, 2007-2016)

	Dependent variable: $\log(TFP_t)$			Dependent variable: $\log(SD_{t-1})$
	(B1.1)	(B1.2)	(B1.3)	(B1.4)
$\log(SD_{t-1})$		0.007	0.008	
		(0.005)	(0.006)	
$\log(STEM_{t-1})$		-0.001***		
		(0.000)		
$\log(STEM_{t-2})$	-0.000		0.005*	-0.002***
	(0.000)		(0.003)	(0.000)
$\log(SD_{t-1}) * \log(STEM_{t-2})$			-0.001**	
			(0.002)	
$\log(HC_{t-1})$	0.002	-0.008	0.010	
	(0.011)	(0.015)	(0.018)	
IM_{t-1}	0.001*	0.001***	0.000	
	(0.000)	(0.000)	(0.000)	
R^2	0.999	0.999	0.999	0.999
$Adj.R^2$	0.999	0.999	0.999	0.999
Observations	108	126	108	126

***Notes*:** $\log(X)$ is log of X; $TFP, SD, STEM, HC$ and IM are TFP, industrial R&D, research scores in science, technology, engineering and mathematics, human capital and import as a share of GDP, respectively. Robust standard errors are in parentheses. *, **, *** indicate parameters that are significant at 10%, 5%, and 1% levels of significance, respectively. All regressions include unreported country-specific and time-specific constants as well as one lead and one lag for cointegrating regressors.

Table B2 reports results on the impact of frontier academic research on TFP using data collected from the university league table published by THE. Because THE did not publish scores associated with the rankings during 2004-2010, our sample is contracted by these seven years to 2011-2017. To capture national frontier academic research for each country, we use the following three indicators in our regressions: (i) CS: citation scores; (ii) RS: research scores (volume, income and reputation); and (iii) RC: research and citation scores (equal to the sum of CS and RS). All regressions include unreported country- and time-specific effects, with human capital stock and import-GDP ratio as control variables. It can be seen that while coefficient estimates for some alternative measures of frontier academic research are statistically significant, that for industrial R&D is insignificant across the regressions. In the meantime, the coefficient of human capital is insignificant and even has a wrong sign (i.e., negative). Similarly, the coefficient of import-GDP ratio is negative and insignificant across regressions. This may be because the time span is too short (i.e. 8 years) to be able to reveal any long-run relationship between the interested variables. The short time span also makes it less meaningful to include any lead and lag structures. As a result, we do not run DOLS regressions, only the OLS regressions, on this reduced-size sample.

Table B2. OLS regression results using THE published university rankings data (two-way fixed effects, 18 countries, 2011-2017)

	Dependent variable: $\log(TFP)$					
	(B2.1)	(B2.2)	(B2.3)	(B2.4)	(B2.5)	(B2.6)
$\log(SD_{t-1})$				0.029	0.033	0.029
				(0.036)	(0.020)	(0.021)
$\log(CS_{t-1})$				0.001^{***}		
				(0.000)		
$\log(RS_{t-1})$					0.002^{***}	
					(0.000)	
$\log(RC_{t-1})$						0.001^{***}
						(0.000)
$\log(CS_{t-2})$	0.000					
	(0.000)					
$\log(RS_{t-2})$		0.001^{***}				
		(0.000)				
$\log(RC_{t-2})$			0.000^{*}			
			(0.000)			
$\log(HC_{t-1})$	-0.033	-0.044	-0.036	-0.030	-0.044	-0.034
	(0.108)	(0.107)	(0.108)	(0.067)	(0.065)	(0.067)
IM_{t-1}	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.847	0.847	0.847	0.809	0.810	0.809
$Adj. R^2$	0.791	0.791	0.791	0.748	0.749	0.748
Observations	90	90	90	108	108	108

***Notes*:** $\log(X)$ is log of X; TFP, SD, CS, RS, RC, HC and IM are TFP, industrial R&D, citation scores, research scores (volume, income and reputation), the sum of both research and citation scores, human capital and import as a share of GDP respectively. Robust standard errors are in parentheses. *, **, *** indicate parameters that are significant at 10%, 5%, and 1% levels of significance, respectively. All regressions include unreported country-specific and time-specific constants.

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