International Journal of Economics and Finance; Vol. 15, No. 11; 2023
ISSN 1916-971X E-ISSN 1916-9728
Published by Canadian Center of Science and Education

Human Capital for Innovation Capacity in Middle-Income Economies

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Received: July 21, 2023 Accepted: September 13, 2023 Online Published: September 25, 2023

doi:10.5539/ijef.v15n11p1 URL: https://doi.org/10.5539/ijef.v15n11p1

Abstract

This paper examines the impact of the human capital composition of unskilled, skilled, and high-skilled levels on the innovation capacity of middle-income economies. Data from 65 countries in lower middle-income, upper middle income, and high-income categories over the period of 1985-2019 is used. Panel data regressions are employed. Results suggest the innovation capacity enhancing effects of high-skilled human capital in upper-middle income countries (UMICs) and high-income countries. For lower middle-income countries (LMICs), the skilled human capital is the important workforce fostering their innovation capacity, while the R&D personnel of high-skilled human capital is yet to be important. Unskilled human capital is confirmed to not play any role in innovation development in MIEs and above. For UMICs, high-skilled human capital is supported by the foreign innovation diffusion through imports, and R&D capital stocks; while for LMICs, FDI-embodied foreign innovation supplements the skilled human capital to build up innovation capacity.

Keywords: Middle-income economies, human capital composition, innovation capacity, panel data regressions

1. Introduction

In growth theories, from the neoclassical growth model to the new growth theory, scholars such as Solow (1956), Nelson and Phelps (1966), Romer (1990), Grossman and Helpman (1991), Aghion and Howitt (1992), etc. have underlined that human capital serves as one determinant for the growth of nations, and it is a prerequisite for economic development. On one hand, human capital might affect the output growth of an economy by serving as labor input in the production function. Researchers often postulate that a more educated and higher skilled workforce would positively associate with growth. On the other hand, according to endogenous growth scholars like Benhabib and Spiegel (1994), Vandenbussche et al. (2006), the stock of human capital might enhance a country's ability to develop local technological innovation and adopt foreign technologies and thereby facilitating convergence. In this approach, technological progress or TFP growth is modeled as a function of the educational level. A higher level of human capital is assumed to better create and implement innovation and enhance absorptive capacity for advanced foreign technologies assimilation as stressed by Keller (2004). The poor quality of human capital might act as a constraint to innovation activities, thus hindering development according to Agénor (2017). Additionally, countries, especially middle-income ones, might not have the capacity to absorb large amounts of physical capital from abroad due to the inadequate supplies of suitable labor.

Despite the dual role of human capital in promoting growth emphasized by authors like Benhabib and Spiegel (1994), Keller (2004), and Kneller and Stevens (2006), the understanding of the effects of human capital at different levels of education and skills on innovation enhancement, especially in middle-income countries remains less prevalent in empirical studies. It is in contrast with numerous papers on the human capital contributions to productivity and economic growth (Agénor & Neanidis, 2015).

Based on the assumption that different levels of development and innovation capacity require different types of human capital, Vandenbussche et al. (2006), de la Fuente and Domenech (2006) further argue that the way human capital composition shapes the innovation capacity might not be uniform. Cross-country analyses leveraging this approach are not abundant according to Ang et al. (2011). Danquah and Amankwah-Amoah (2017) and Qureshi et al. (2021) review that among those few studies, the focus is mainly on developed economies like the OECD that are closer to the technological frontier and have more stable institutional system. The understanding of how human capital composition enhances innovation in catch-up economies remains limited.

As an effort to narrow the research gap above, this study aims to examine the innovation enhancing effect of human capital composition in MIEs. Using panel data at the aggregate national level of 65 countries during the period from 1985 to 2019 that covers MIEs and above, with a focus on middle-income ones, the paper explores the role played by unskilled, skilled, and high-skilled levels of human capital on the innovation capacity of these countries. The panel data regression estimation procedures are applied on the dataset of this study.

Empirical results of this study show that unskilled human capital is not significant to the innovation capacity of middle-income and high-income countries. Skilled human capital is important for the innovation capacity of lower middle-income countries (LMICs) while being unimportant to upper middle-income countries (UMICs) and high-income countries (HICs). On the contrary, high-skilled human capital is positively significant to the innovation capacity of both UMI and HI groups. Aside from skilled human capital, foreign innovation embodied in the FDI channel is also crucial for LMICs. R&D capital stock and import-embodied international R&D spillover are found to support innovation capacity in UMICs. In HICs, findings highlight the important role of R&D personnel is supported by R&D capital stock, FDI embodied foreign innovation and the institutional quality.

The contribution of this study is threefold. First, it contributes to the literature on the role of human capital for innovation at aggregate level. Second, it expands empirical results on the innovation-enhancing effect of the human capital composition. This study postulates that the composition of human capital based on the educational level is insufficient to reflect the importance of human capital to innovation capacity. The categories of skilled human capital proxied through tertiary education, and unskilled human capital proxied through primary and secondary education by Vandenbussche et al. (2006), Ang et al. (2011), and Agénor and Neanidis (2015) are supplemented by the high-skilled human capital of R&D personnel in this study. As the direct labor force involved in innovation activities, R&D personnel, might represent more accurately the vital role of human capital composition for innovation capacity. To the best of the author’s knowledge, this is the first attempt to examine the impact of human capital composition on innovation at the aggregate level using these three components of unskilled, skilled, and high-skilled human capital. The inclusion of high-skilled human capital in addition to the educational outcome variables of unskilled and skilled human capital is another uniqueness of the study. Third, this study extends the empirical findings on MIEs by including 44 middle-income countries in the sample of 65 economies. Utilizing aggregate data at the national level is another contribution in this regard given the more prevalent firm-level innovation data in current studies.

The paper continues as follows. The next section reviews the literature on the role of human capital and innovation in economic development, and the study gap on the impact of human capital composition on innovation capacity. Section 3 explains the methodology approach, including a framework of research, estimation strategy, and data used in this study. Section 4 details estimation results together with the robustness check. Conclusions and implications of results to policies are made in section 5.

2. Literature Review

2.1 The Role of Human Capital and Innovation in Growth Literature

Human capital is considered an important driver of economic growth, and innovation is another vital component of economic development in neoclassical growth models and endogenous growth theories as reviewed by Ang et al. (2011) and Agénor and Neanidis (2015). The link between human capital, innovation, and growth has been the subject of numerous theoretical and empirical studies. Starting from Solow (1956), other scholars like Romer (1990), Grossman and Helpman (1991), Aghion and Howitt (1992) and (1998) have considered R&D or technological advancement and human capital accumulation as engines of growth by emphasizing the complementarity between these two components of the development process.

Human capital is usually referred to as knowledge, skills, competencies, and attributes embodied in individuals as defined by Becker (1964). Goldin (2016) explains that knowledge and skills that are part of human capital are acquired through education and experience. It is in the same line as Becker (1964) who provides a general theory on the role of human capital in the production process and the incentives to invest in skills, from pre-labor market investments in the form of schooling to investment in on-the-job training. The contribution of human capital in enhancing innovation and economic growth is largely emphasized in these studies. Manca (2012) reviews that human capital is appropriate to represent the absorptive capacity of firms and countries. Danquah and Amankwah-Amoah reasons that human capital can be utilized to foster innovation activity (2017). More specifically, as elaborated by Deakins and Whittam (2000), at the organizational level, human capital might be associated with the ability to develop business innovation in a firm, or the ability to execute and implement policies in public sector agencies.

Along with human capital, innovation emerges as one important driver stimulating economic development in the neoclassical growth model and endogenous growth theory. Innovation might be recognized as an engine of economic growth, especially for MIEs whose marginal productivity of capital accumulation is diminishing and are seeking new drivers of growth. Types and sources of innovation play different roles across income levels or economic development stages. Fagerberg and Verspagen (2002) reason that countries in early stages of development leverage foreign technologies adoptions, while at later stages of development and relatively closer to the technological frontier, countries leverage indigenous innovation efforts. Similar to this conclusion, Blyde (2003) views that international R&D spillovers are a relatively more important source of productivity gains for developing than for developed or high-income countries. On the contrary, findings by Santacreu (2015) show that growth of developed countries is attributed mainly to domestic innovation.

Scholars often assume that there is a strong connection between innovation and human capital to enhance national-level development. Innovation, a knowledge-intensive activity, depends on human capital to generate ideas and apply knowledge (Mourad & Dirk, 2004). Human capital is among the determinant of an economy’s capacity to carry out technological innovation and adopt foreign technologies. Nelson and Phelps (1966) reason that the more educated the labor force, the faster the adoption of new technologies. Historically, in the 1950s, the neoclassical growth model by Solow-Swan postulates that the aggregate outputs are produced through a production function of labor and capital. In the long run, a steady-equilibrium economy must rely on innovation as an exogenous source of growth. In the 1990s, endogenous growth economists such as Romer (1990) and Aghion and Howitt (1992) emphasize that technological innovation is determined endogenously within the model from the rate of investment, the size of the capital, and human capital stock, etc. Innovation in R&D sectors uses human capital and existing knowledge stock, and human capital determines the capacity of a nation to innovate as explained by Romer (1990). Human capital promotes productivity growth through facilitating the development of new technologies for domestic innovation, as well as diffusing and adopting new foreign technologies as highlighted by Grossman and Helpman (1991c) and Aghion and Howitt (1992). Keller (2004) elaborates that the successful adoption of foreign technology also requires firms and countries to have certain types of skills.

The contribution of human capital and innovation to growth has been the focus in economic development theories. Human capital serves as labor input in the production function and directly affects economic growth. Indirectly, one might reason that human capital contributes to growth through enhancing innovation for higher technological progress as reviewed by Ang, Madsen, and Islam (2011). The dual role of human capital is supported by Keller (2004) and Kneller and Stevens (2006). The link between human capital, innovation, and economic growth has been the subject of numerous theoretical and empirical growth literature, in which the contributions of human capital and innovation to growth are estimated (Agénor & Neanidis, 2015). However, the direct relationship between human capital and innovation has not been the focus especially for MIEs, except for a few studies such as by Mourad and Dirk (2004), Stone and Shepherd (2011). In support of this argument, Danquah and Amankwah-Amoah (2017) view that the understanding of how human capital enhances innovations, especially in developing countries remains limited. Qureshi et al. (2021) review that most empirical analyses focused on developed countries which are at or near the global technological frontier, and few analyses delve into innovation patterns in catch-up economies. To contribute to closing this gap, in this paper, the research question is formulated as: “How does human capital affect the innovation outputs of MIEs?”

2.2 Innovation Capacity Enhancing Effects of Human Capital Composition

Given the importance, while limitedly studied of the direct relationship between human capital and innovation capacity as reviewed in section 2.1, the review of studies on the link between human capital and innovation, especially in MIEs is made in the following section.

Empirical studies on human capital contribution to innovation capacity show mixed findings. Mourad and Dirk (2004) find a positive relationship between human capital proxied through HDI and innovation proxied through patent counts, R&D expenditures, and high-tech export in a study of 59 economies between 1995 and 2004. The results provide significant support to the role of human capital as a catalyst for innovation. Stone and Shepherd (2011) conclude that skilled labor is a crucial determinant of a firm’s ability to realize productivity gains. Danquah and Amankwah-Amoah (2017) measure effects of human capital on innovation and technology adoption in 83 countries between 1960 and 2010. Human capital measured by mean years of schooling in the population aged 15 years and over appears to generate a positive and significant impact on the adoption of technology, while its impact on domestic innovation is insignificant.

Given the stylized fact on the underscored role of human capital for innovation in growth theories, the mixed results on the contribution of human capital to innovation are puzzling. It is similar to the problem some scholars face when estimating the contribution of human capital to economic growth using the average human capital stock. For example, Krueger and Lindahl (2001) question the assumption in the influential model of Mincer that the change in a country's average level of schooling should be the key determinant of income growth. De la Fuente and Domenech (2006), Vandenbussche, Aghion and Megh (Vandenbussche, Aghion, and Megh, 2006), and Cohen and Soto (2007) by determining a weak correlation between variables of education and economic growth raise skepticism about the relevance of average human capital measures in explaining the growth process.

To solve this puzzle, Vandenbussche, Aghion, and Megh (2006) postulate that the growth-enhancing effects of human capital depend on its composition rather than on the average measure of human capital stock. Different human capital skill levels of workers may differently interact with economic growth. At each development stage, or depending on the distance from the technological frontier, a country might find the significant contribution of each human capital component differently. For lower-income countries, incremental innovation and dependence on technological diffusion are often observed. Incremental innovation is postulated to be low-skilled and labor-intensive. However, when an economy approaches the world technologies frontier, groundbreaking innovation is the main engine of growth and requires higher-skilled labor. Empirically, Benhabib and Spiegel (2005) study the sample of 19 OECD countries between 1960 and 2000 and find that the growth-enhancing effect comes from skilled human capital of tertiary education attainment, rather than coming from total average human capital. Manca (2012) suggests that the developed regions succeeding in changing the human capital composition by increasing the share of highly educated workers close the gap with the technological frontier faster. Ang, Madsen, and Islam (2011) conclude that the effect of skilled human capital is increasing with proximity to the technological frontier since highly innovative economies are also highly skilled-intensive.

There are limited studies analyzing the human capital composition effect on the growth of countries at different income levels as noted by Ang, Madsen, and Islam (2011). Human capital composition effect is mainly studied in developed countries like the OECD. Fewer studies on the innovation capacity enhancing effect of human capital composition are found for developing countries. Among these few, Agénor (2017) reasons that in early stages of development, high-skilled labor matters relatively little, but will become more important when countries advance closer to the technologies frontier and compete intensively against foreign competitors. In UMICs, returns to high-skilled workers may be higher than those of low-skilled workers according to Aghion et al. (2009). Danquah and Amankwah-Amoah (2017) assume that tertiary education and above is crucial for technological innovation as the more educated labor force, the easier it is to master technologies. The adoption and implementation of technology from frontier technology still require high-skilled workers as it's a skill-costly activity according to Manca (2012).

In a few studies on innovation enhancing effect of human capital at different education levels, Vandenbussche et al. (2006), Ang, Madsen, and Islam (2011), and Agénor and Neanidis (2015) human capital level is decomposed into unskilled human capital measured by primary and secondary education completion rate, and skilled human capital is proxied through tertiary education completion rate. However, educational outcomes might not be sufficiently representative of human capital impacts on innovation capacity, and that tertiary education is not a good enough measure of the high-skilled workforce that can contribute to innovation. There is a gap between the use of human capital education attainment variables and the knowledge and skills of workers in the innovation process.

To address this issue, in this paper, it's reasoned that human capital in R&D sectors or R&D personnel might better represent the human capital necessary for groundbreaking innovation and more accurately reflect the knowledge, skills, and competence required as inputs in the innovation process. Human capital in R&D sectors is categorized as high-skilled human capital measured by the number of R&D personnel per million population. This study differentiates itself from the existing ones which assume that tertiary education is sufficient human capital for innovation.

Based on the review of human capital composition effects on different income categories, and the composition of human capital assumed in this study, the following hypotheses are made.

Hypothesis 1: Skilled human capital is more important for the innovation outputs of LMICs.

Hypothesis 2: High-skilled human capital contributes more to the innovation outputs of UMICs.

Hypothesis 3: Unskilled human capital is not important for innovation outputs of MIEs.

In the next session, the methodology approach to verify the research question and confirm these hypotheses will be presented.

3. Empirical Methodology

In this section, the methodology approach to examine the impact of different levels of human capital on innovation that was posed in the research question and its three hypotheses is presented. The estimation design and panel data estimators are described. The data, its sources, and descriptive statistic are introduced next.

3.1 Model specification and Estimation Strategy

To examine the innovation-enhancing effect of human capital composition in different subcategories of middle-income, this study included three categories of unskilled, skilled, and high-skilled human capital as analyzed in subsection 2.2. It is the expansion of human capital composition in existing empirical studies. The estimation equation takes the following functional form to depict the relationship between the human capital composition and innovation capacity:

$$inno_{it} = \beta_1 hc\_usk_{it} + \beta_2 hc\_sk_{it} + \beta_3 hc\_hs_{it} + \theta' X_{it} + \mu_i + \eta_t + \varepsilon_{it} \quad (1)$$

In which *i* denotes country and *t* denotes time; dependent variable of $inno_{it}$ denotes innovation capacity measured by annual patent application number; hc_usk_{it} proxies unskilled human capital; hc_sk_{it} represents skilled human capital; and hc_hs_{it} denotes high-skilled human capital; X_{it} is a vector of control variables that include R&D capital stocks, foreign innovation embodied in FDI and import channels; and quality of institution; μ_i denotes country-specific fixed effects; η_t captures the unobservable individual invariant time effect; and ε_{it} is error term. Constant terms are also included in these estimations.

Panel data regression is employed in these estimations for each subgroup of LMICs, UMICs, and HICs following Qureshi et al. (2021) and Agénor and Neanidis (2015). Unobserved country-specific effects and time-invariant effects are controlled for in these panel data regressions by including country and year dummies.

The Hausman test (Hausman, 1978) is conducted to choose the more relevant models among the FEM and REM. The null hypothesis under the Hausman test is that there is no correlation between the individual effects and the independent variables. The Hausman test result with the chi-square value and its p-value of less than 5% would reject the null hypothesis and confirms the more efficient FEM. An insignificant value of this test would indicate the REM outperforms the FEM. In case the null hypothesis cannot be rejected and confirm the choice of REM, the Lagrange Multiplier (L-M) test following Breusch and Pagan (1980) is conducted. The L-M test results would determine whether the REM or Pooled OLS is more relevant. If the null hypothesis of the test is rejected, REM is indicated to outperform Pooled OLS. In case FEM is found to better fit, F-test results to confirm the relevance of FEM over Pool OLS is necessary. The elaboration on constructions of variables in the estimation equation above and its data sources will follow in the next section.

3.2 Variables Construction

This section elaborates on the dependent variable of innovation capacity, human capital composition variables of skilled, skilled, and high-skilled human capital, the control variables of R&D investment, FDI-embodied and import-embodied foreign innovation, and institutional quality will be made.

3.2.1 Measurement of Innovation Capacity – A Dependent Variable

The dependent variable of innovation capacity is measured by patent applications of residents. The use of patent data in the analysis of innovation is due to its advantages in systematically archived for long time series and across countries. It also represents part of the output of innovation generated from innovation input of R&D investment at the aggregate national level. Patent application data are more comparable across countries than patent grants which are heavily depending on the characteristics of each country's patent examination systems following Eaton and Kortum (1999). Data on patent applications of residents is from the database of WIPO and adjusted by million population.

3.2.2 Human Capital Composition – Explanatory Variables

In human capital measurement, educational data is often used because it's a simple approach while education is one of the most important characteristics embodied in workers as reviewed by Collins and Bosworth (1996). Estimating the impact of human capital on economic growth, previous studies might use education indicators of enrollment rate, average years of schooling, literacy rates such as in Barror and Lee (2013), Caselli, Esquivel, and Lefort (1996), cognitive skills measured by test score in Eric and Woessman (2012). While enrollment ratios represent human capital investment levels, literacy is a stock variable for human capital (Benhabib & Spiegel, 1994).

In this study, human capital is constructed as the fraction of the population having primary, secondary, and tertiary education following Ang, Madsen, and Islam (2011). Moreover, it's postulated that the human capital composition based on the educational level is insufficient to reflect the role of human capital to innovation output. The high-skilled human capital of R&D personnel, the direct capital for the innovation process, is assumed to be more relevant. R&D personnel characterizes a key innovation input as it includes professionals who conduct research and improve or develop concepts, theories, models, techniques, instrumentation, and software of operational methods. R&D personnel supplements the skilled and unskilled human capital (Qureshi, Park, Crespi, & Benavente , 2021).

Unskilled Human Capital

The total primary and secondary education share in the population represents the unskilled human capital. The unskilled human capital variable is constructed based on the dataset of Barro and Lee (2013). The dataset has been updated online until September 2021.

Skilled Human Capital

To move up the value chain beyond simple production processes and products, higher education completion labor force is crucial. In this study, it is used as a proxy for skilled human capital. Tertiary education, even though not high-skilled, plays a crucial role in the exchange of ideas and skills necessary for innovation. The skilled human capital is measured by the fraction of the population over the age of 15 completing tertiary education in the dataset of Barro and Lee (2013).

High-Skilled Human Capital

Aside from education, the level and standard of research activity in an economy are prime determinants of the innovation capacity of a nation. Human capital employed in R&D sectors serves as direct human capital inputs for innovation activities. R&D personnel consists of people performing R&D, highly trained scientists, and engineers (researchers), technicians with a high level of experience and training, and supporting staff who contribute directly to carrying out R&D activities (OECD/Eurostat, 2018). In this study, high-skilled human capital is measured by the number of R&D personnel full-time equivalent (FTE) as a proportion of the population extracted from UNESCO Statistics and UN Statistical Yearbooks.

3.2.3 Control Variables

The following control variables are included in the regressions: R&D capital stocks; FDI- and import-embodied foreign innovation; and institutional quality.

R&D Capital Stock Per Capita

R&D variable as input of innovation to account for knowledge stocks in the R&D sector. R&D investment is required for developing new technologies and enabling a firm or country to understand and adopt innovation appropriately (Keller, 2004). R&D capital stock is calculated based on the gross expenditure on R&D by applying the perpetual inventory method (PIM) (Coe & Helpman, 1995) as follows.

$$R\&D_S^{t+1} = (1-\delta)\, R\&D_S^t + R\&D_{exp}^t \tag{2}$$

where $R\&D_S^{t+1}$ is R&D capital stock of a country in year t+1; $R\&D_S^t$ refers to the initial value of R&D capital stock in year t (Note 1); $R\&D_{exp}^t$ is R&D expenditure of a country in year t; and δ is the annual R&D capital depreciation rate of 5% following Coe and Helpman (1995) and Litchtenberge and Pottelsbergh (1998). R&D capital stock data is normalized by population to account for the scale effect of economy size.

Foreign R&D Capital Stock per Capita Embodied in FDI and Imports

Foreign innovation of a country is constructed as weighted sums of R&D capital stocks of its foreign partners. The weighting scheme for foreign innovation embodied in FDI and imports follows Litchtenberge and Pottelsbergh (1998) in this study with the following formulas.

Foreign R&D capital stock embodied in inward FDI:

$$FI_{At}^{FDI} = \sum_{B=1}^{x} FDI_{ABt} \ \frac{DI_{Bt}}{GDP_{Bt}};\ A \neq B. \tag{3}$$

Import-embodied foreign R&D stock:

$$FI_{At}^{IMP} = \sum_{B=1}^{x} IMP_{ABt} \ \frac{DI_B^t}{GDP_{Bt}}\ ;\ A \neq B \tag{4}$$

where foreign innovation effort of country A at time *t* embodied in FDI inflow is FI_{At}^{FDI} and in imports is FI_{At}^{IMP}; FDI_{ABt} refers to the stock of inward FDI and IMP_{ABt} refers to bilateral imports of country A from country B at time *t*; GDP and R&D capital stocks of country B are denoted as GDP_{Bt} and DI_{Bt}.

Institutional Quality

The innovation capacity of a country is highly affected by its institutional quality such as the rule of law, regulatory agencies, intellectual property rights, etc. The index of legal structure and property rights (Note 2) is extracted from the dataset of the Economic Freedom of the World published by the Fraser Institute to reflect institutional quality of the participating economies. Among various indices for institutional quality, this dataset is used since it covers a wide range of countries throughout the period of 1985-2019.

3.3 Data

The data span 65 countries for the periods of 1985–2019 (a list of countries in each income group is given in Appendix 1). Data of 5-year average for seven periods, i.e., 1985-1989, 1990-1994, 1995-1999, 2000-2004, 2005-2009, 2010-2014, 2015-2019, is constructed to reduce potential volatility and provide a solution to miss-data issue, especially for LMICs. This implies a maximum size of 455 observations for the full sample of all countries. The sample is divided into three groups of income of LMICs, UMICs, and HICs. The classification is based on the data of GNI per capita by the World Bank, 2020. The summary of variables and data sources are presented in Table 1.

Table 1. Summary of variables and data sources

Variable	Explanation	Data source
Dependent variable		
Patents (log value) (lnpat)	Number of resident patent applications per million population	WIPO
Explanatory variables		
Unskilled human capital (log value) (lnhc_usk)	Number of people above 15 years of age attained primary and secondary education levels per million population	Barro and Lee (2013) and its online updated dataset until 2021.
Skilled human capital (log value) (lnhc_sk)	Number of people above 15 years of age attained tertiary education level per million population	
High-skilled human capital (log value) (lnhc_hs)	Number of full-time equivalent (FTE) R&D personnel per million population	UNESCO Institute of Statistic and UN Statistical Yearbook
Control variables		
R&D capital (log value) (lnrd)	Domestic R&D capital stock per capita, annual value calculated from GERD recorded at the beginning of the year. Unit: USD, constant 2010 prices.	UNESCO Institute of Statistic and UN Statistical Yearbook
FDI-embodied foreign innovation (log value) (lnfdi)	Foreign R&D capital stock per capita embodied in inward FDI, from TRIAD. Unit: USD, constant 2010 prices.	UNCTAD and UN Comtrade Database
Import-embodied foreign innovation (log value) (lnimp)	Foreign R&D capital stock per capita embodied in imports, from TRIAD. Unit: USD, constant 2010 prices.	
Institutional quality (inst)	Quality of institutions in an economy, measured through the legal structure and property rights index.	Economic Freedom of the World

4. Estimation Results

In this section, estimation results based on the methodology in the previous section are presented. The relationship between the human capital composition of unskilled, skilled, and high-skilled to innovation capacity are estimated while controlling for the effects of R&D capital stocks, FDI- and import-embodied foreign innovation, and the instructional quality. To assess the robustness of these results, tests are then conducted with alternative measures of human capital composition and innovation capacity.

4.1 Descriptive Statistics

Descriptive statistics for patents and human capital composition of unskilled, skilled, and high-skilled levels during the period of 1985-2019 across the three income groups are presented in Table 2.

Among 65 countries included in the study, there are 18 LMICs, 26 UMICs, and 21 HICs. Data on patent applications of residents show that maximum value belongs to the group of HICs, followed by UMICs and LMICs. Details on distribution of patent applications across different income groups is depicted in Figure 1. Similar to the data on patents, the maximum value of R&D capital stock per capita, institutional quality, high-skilled human capital, skilled human capital, and unskilled human capital of HICs are greater than UMICs. Those values of UMICs are greater than those of LMICs. Comparison of mean value of different human capital skill levels across the three income groups show similar pattern (Figure 2), and available in full in Appendixes 2, 3, 4, and 5.

Table 2. Descriptive statistics

Variables	Observations	Mean	Standard Deviation	Min.	Max.
LMICs (18 countries)					
lnpat	120	0.671	1.732	-4.843	3.674
lnhc_usk	126	10.575	0.930	7.378	12.520
lnhc_sk	119	8.065	0.494	6.532	9.167
lnhc_hs	92	6.078	1.132	3.305	8.524
lnrd	95	3.116	1.435	-0.296	5.567
lnfdi	121	2.506	1.712	0.001	6.681
lnimp	126	2.010	1.263	0.000	4.547
inst	126	4.324	0.857	2.527	5.872
UMICs (26 countries)					
lnpat	178	2.570	1.200	0.008	5.626
lnhc_usk	174	11.808	0.952	8.517	13.102
lnhc_sk	182	10.869	1.000	4.605	12.527
lnhc_hs	182	6.557	1.162	4.102	9.246
lnrd	178	5.747	0.976	2.889	8.206
lnfdi	180	3.789	1.714	-0.991	7.029
lnimp	181	4.342	1.078	1.526	6.434
inst	180	4.943	0.795	2.000	6.950
HICs (21 countries)					
lnpat	144	4.715	1.703	-0.089	8.071
lnhc_usk	147	12.720	0.430	11.491	13.490
lnhc_sk	147	13.151	0.223	12.596	13.663
lnhc_hs	147	7.909	1.044	5.085	9.856
lnrd	142	6.986	1.377	2.759	9.555
lnfdi	138	5.763	1.109	2.541	8.519
lnimp	145	5.014	1.246	2.102	7.785
inst	147	6.367	0.923	3.570	7.981
All countries (65 countries)					
lnpat	442	2.792	2.175	-4.843	8.071
lnhc_usk	447	2.550	1.165	7.378	13.490
lnhc_sk	448	2.893	1.244	4.605	13.663
lnhc_hs	421	6.946	1.348	3.305	9.856
lnrd	415	5.660	1.856	-0.296	9.555
lnfdi	426	4.050	2.005	-0.991	8.519
lnimp	431	3.966	1.648	0.000	7.785
inst	452	5.231	1.186	2.000	7.981

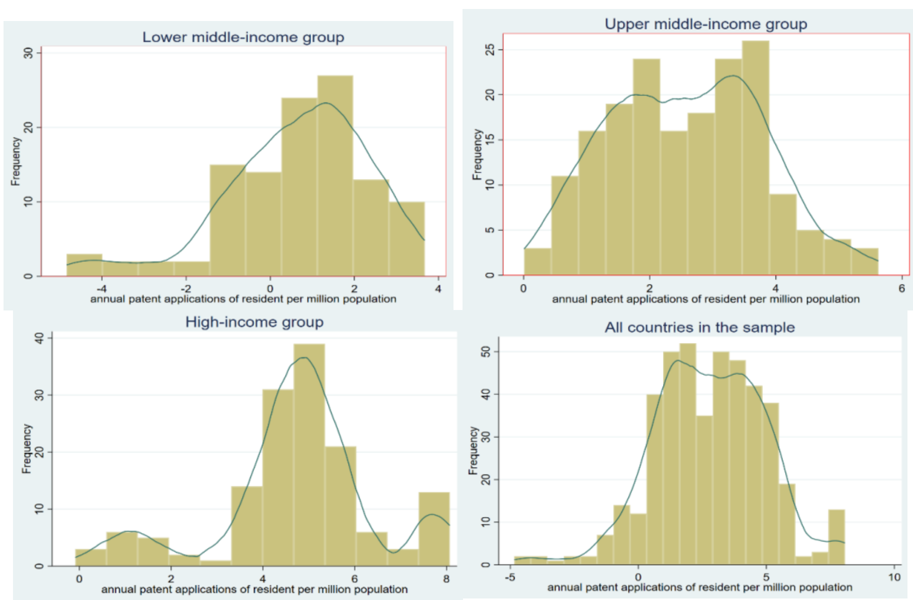

Figure 1. Distribution of patent applications across different income groups

Source: Author's calculation.

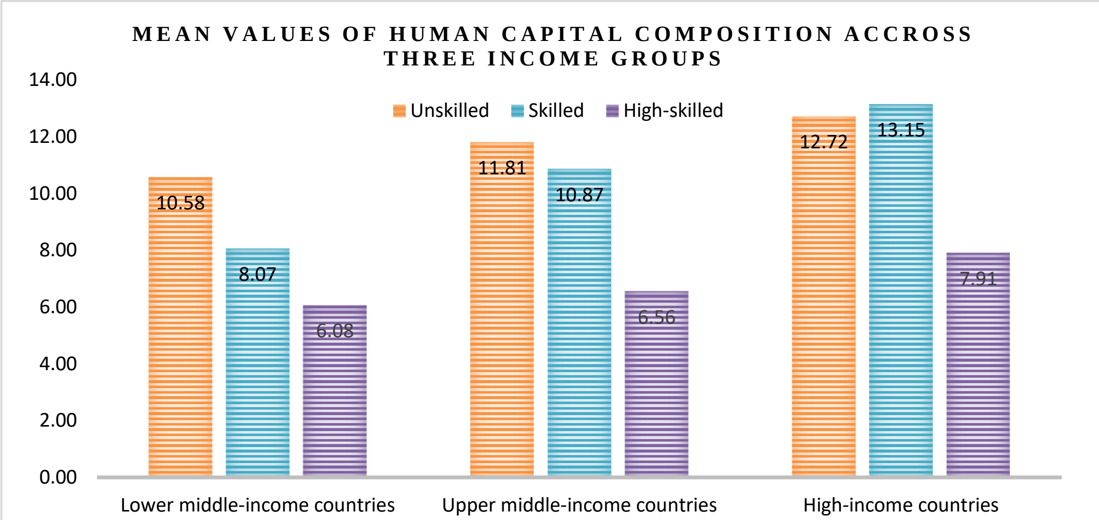

Figure 2. Mean value of human capital composition across three income groups

Source: Author's calculation.

Preliminary observation on data show that there exists a positive correlation between human capital composition variables and the innovation output variables. This pattern applies for unskilled, skilled, and high-skilled human capital variables across three income groups.

Correlation metrics for the variables for each group of LMICs, UMICs, HICs, and a full sample of all countries are described from Table 3 to Table 6 below. In these tables, no high correlation coefficients among variables are found. Thus, multicollinearity should not be an issue in the estimations.

4.2 Main Results

In this section, the analysis of the impact of different human capital skill groups on the innovation capacity of LMICs, UMICs is presented.

The result of the Hausman test in Table 3 rejects the null hypothesis. The Chi-square value ranges from 22.10 (LMICs) to 63.62 (UMICs) in those four models, with significant p-values of less than 5% of this test for regression of LMICs, UMICs, HICs, and all countries. The results of the Hausman tests indicate that the FEM is more efficient for the samples of this study and outperforms the REM in these estimations.

Table 1. Results of Hausman tests for FEM vs. REM

	Lower Middle-income	Upper Middle-Income	High-Income	All Countries
Chi-square test value	22.10	63.62	25.58	27.01
P-value	0.037	0.000	0.019	0.012

To confirm the fit of FEM over the Pooled OLS model, the results of F test for u_i=0, or to confirm the null hypothesis that Pool OLS is more efficient than REM is presented is conducted. The results of the F test support that FEM is more efficient than the Pooled OLS with significant p-values of less than 1% in all models (Table 4). Thus, the null hypothesis is rejected, and FEM is concluded to be more appropriate than Pooled OLS model in this study.

Table 2. Results of F tests that all u_i=0 for FEM vs. Pooled OLS models

	Lower Middle-income	Upper Middle-Income	High-Income	All Countries
Chibar2	32.08	18.25	15.41	20.18
P-value	0.000	0.000	0.000	0.000

The results of the estimated panel FEM are presented in Table 5 for four groups of LMICs, UMICs, HICs, and all countries. The results in Table 5 show that unskilled human capital is insignificant to all groups of LMICs, UMICs, and HICs. The effect of skilled human capital is only significant and positive for LMICs. On the contrary, high-skilled human capital is statistically significant for UMICs and HICs. In Table 5, results of both FEM and REM are presented. Even though FEM is found to be relevant to the dataset of this study, the identical result estimations of both FEM and REM support the robustness of the results.

4.2.1 Lower Middle-Income Countries

In model 1 of Table 5, results for the group of LMICs show that among human capital variables, only the skilled human capital of tertiary education completion workforce is statistically significant for innovation capacity at 1% significance level. The positive and significant coefficient of skilled human capital infers that for LMICs who have just moved away from the low-income level and are still technology followers, to efficiently assimilate foreign advanced technologies and adapt to local conditions, the skilled workforce is the most important. The unskilled human capital of primary and secondary education completion at the basic education level is not required for enhancing innovation in LMICs (Manca, 2012). However, the high-skilled human capital promoting innovation of new technology is yet to be required. R&D personnel or high-skilled human capital is yet to show its importance since the innovation is not yet at the groundbreaking level. Hypothesis 1 is confirmed.

The important role of the skilled human capital of tertiary education for LMICs to facilitate the diffusion of technologies echoes the conclusion of Aghion et al. (2009) that in LMICs, the returns to lower-skilled workers is higher than those of high-skilled workers. It is contrary to Ang, Madsen and Islam (2011) who demonstrate that the innovation-enhancing effect of tertiary education attainment is generated only in high-income countries, while it does not contribute to innovation- and growth-enhancing effects in LMICs.

The results of the insignificant role of the unskilled and significant role of the skilled human capital in LMICs might be explained by Vandenbussche et al. (2006) who propose that the marginal increase in the unskilled human capital enhances productivity growth when a country is further away from the technology front runner, and tertiary education is increasingly important for growth when a country gets closer to the technological frontier according to Ang, Madsen, and Islam (2011).

The coefficient of FDI-embodied foreign innovation is positive and significant at 1% significance level. The importance of the FDI channel is similar to the results of studies by Blyde (2003), Crispolti and Marconi (2005), and Ang and Madsen (2013). The import-embodied foreign innovation is found not significant for LMICs. The results may reflect that the spillover effect of innovation resulting from foreign trade is limited. It can be assumed that the import channel is not effective in transferring foreign innovation may be due to the lack of matching local absorptive capacity.

Table 3. Estimation results of human capital composition effects on innovation capacity

Dependent variable: resident patent application (lnpat)	Model 1: Lower Middle-income		Model 2: Upper Middle-Income		Model 3: High-Income		Model 4: All Countries	
	FE	RE	FE	RE	FE	RE	FE	RE
Unskilled human capital	-0.022	0.032	0.004	-0.132	-0.283	0.350	-0.062	0.007
(lnhc_usk)	(0.314)	(0.348)	(0.097)	(0.134)	(0.072)	(0.481)	(0.155)	(0.121)
Skilled-human capital	**1.801*** **	**1.337*** **	0.047	0.002	-0.498	-0.863	0.040	0.049
(lnhc_sk)	**(0.443)**	**(0.344)**	(0.055)	(0.048)	(0.720)	(0.805)	(0.076)	(0.073)
High-skilled human capital	0.116	0.096	**0.211** **	**0.259*** **	**0.638* **	**0.568** **	**0.297*** **	**0.324*** **
(lnhc_hs)	(0.151)	(0.104)	**(0.093)**	**(0.076)**	**(0.354)**	**(0.237)**	**(0.087)**	**(0.078)**
R&D capital (lnrd)	0.154	0.356	**0.306** **	**0.322*** **	**0.257** **	**0.345*** **	**0.300*** **	**0.406*** **
	(0.176)	(0.222)	**(0.141)**	**(0.124)**	**(0.105)**	**(0.103)**	**(0.093)**	**(0.088)**
FDI-embodied foreign	**0.302*** **	**0.359** **	-0.057	-0.067	**0.349** **	**0.325** **	**0.156*** **	**0.232*** **
innovation (lnfdi)	**(0.097)**	**(0.150)**	(0.099)	(0.076)	**(0.143)**	**(0.131)**	**(0.058)**	**(0.056)**
Import-embodied foreign	-0.112	0.001	**0.380** **	**0.274* **	-0.189	-0.208	-0.020	0.037
innovation (lnimp)	(0.177)	(0.239)	**(0.176)**	**(0.153)**	(0.196)	(0.175)	(0.125)	(0.101)
Institutional quality (inst)	0.171	0.207	0.030	0.274	**0.502** **	**0.410*** **	**0.156* **	**0.186* **
	(0.173)	(0.211)	(0.055)	(0.153)	**(0.187)**	**(0.147)**	**(0.106)**	**(0.099)**
Constant	-15.284	-12.891	-2.911	-0.809	4.092	1.911	2.040	-3.532
	(3.090)	(3.670)	(1.229)	(1.791)	(0.580)	(0.653)	(0.944)	(0.592)
No. of observations	90	90	174	174	138	138	413	413
No. of groups	17	17	26	26	21	21	63	63
F test/ WaldChi2	274.99	304.63	36.78	234.81	14.29	407.23	216.00	240.06
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

R-squared (overall)	0.249	0.364	0.345	0.478	0.555	0.661	0.676	0.730
R-squared (within)	0.611	0.577	0.726	0.715	0.534	0.715	0.261	0.456
R-squared (between)	0.218	0.423	0.221	0.391	0.607	0.509	0.712	0.758
Country fixed effects	Yes		Yes		Yes		Yes	
Time fixed effects	Yes		Yes		Yes		Yes	

Note. Coefficients are reported with robust standard errors in parentheses. P-values: *p<0.10; **p<0.05; ***p<0.01.

4.2.2 Upper Middle-Income Countries

In model 2 (Table 5), results for UMICs show that similar to the LMIC group, unskilled human capital is statistically insignificant to the innovation capacity of UMICs. However, skilled human capital no longer plays an important role in UMICs' innovation level. The coefficient of the high-skilled human capital of R&D personnel is positive and significant to the innovation capacity of UMICs at 10% significance level in FEM. It can be presumed that UMICs have moved up the income ladder and reached a certain level of innovation capacity, therefore, to foster technological innovations and adopt foreign innovation for UMI group, R&D personnel roles is exceeding the role of unskilled and skilled workers. These results support the finding of Vandenbussche et al. (2006) in which the highly educated workforce is the main driver of growth and innovation. However, it's contrary to this study that high-skilled people are considered R&D personnel, while others considered tertiary education is highly skilled. Similarly in a study using patent application aggregate level data of 17 OECD countries between 1973 and 2006, Furman, Porter, and Stern (2002) conclude that R&D personnel or human capital in the R&D sector is positively significant to innovative capacity proxied through patents applications. Innovation capacity is driven by R&D manpower. It's contrary to the finding of Ulku (2007) who use aggregate patent and R&D data in 41 countries and find that the increase in the ratio of researchers to total labor forces increases innovation in only the large market of OECD countries. Hypothesis 2 is confirmed by these results.

High-skilled human capital possesses a sufficient level of skills to exploit the sophisticated tools and techniques, and latest technologies and therefore contribute positively to the enhancement of national aggregate innovation capacity. UMICs that need to implement cutting-edge technologies to converge with the high-income group, and HICs that need to maintain their indigenous innovation capability require more R&D personnel and high-skilled personnel with more technical and specialized education. High-skilled human capital might ease the adoption of new technologies from foreign partners, with sophisticated technology transfers and diffusion.

The coefficient for import-embodied foreign innovation is positive and significant at 5% level. The result of a positive and significant impact of R&D capital stock at 5% level of significance underlies the role of R&D capital stocks that are prevalent in empirical studies on economic development. It can be postulated that the innovation spillover effect of high technologies through imports and its adoption in UMICs required a sufficient level of absorptive capacity. The role of the import channel in diffusing the R&D of foreign partners is similarly concluded by Coe and Helpman (1995; 2009), Xu and Wang (2001), Crispolti and Marconi (2005), and Ang and Madsen (2013).

The findings of the unimportant of unskilled human capital for LMICs and UMICs confirm hypothesis 3, which is also the same as the conclusion of Agénor (2017) that primary and secondary education measures do not matter significantly for innovation capacity. Unskilled human capital with a basic level of capacity to utilize information might be more relevant for imitation in low-income economies than innovation in MIEs.

Expanding the estimation results on the role of the human capital level of education and skills to the group of HICs and all countries in model 3 and 4, the robustness of the results are confirmed. Unskilled human capital is repeatedly insignificant in regression for both HICs and all countries. For HICs, the high-skilled human capital of R&D personnel is the only important group among the labor force. Its p-value of the coefficient is positive and significant at 10%. Together with high-skilled human capital, R&D capital stocks, FDI embodied foreign innovation, and the quality of institution is also vital for strengthening the innovation capacity of HICs. These results are confirming the assumption on the role of R&D and institutional quality in the most empirical study for HICs development. While R&D and institutional quality are vastly recognized in the literature for its innovation-enhancing effects, the positive and significant role of FDI-embodied foreign innovation found in this research is not consistent in existing literature. Xu (2000) explains that in the case of HICs, the FDI channel transfers the more complex technology that might require a certain level of human capital quality to absorb and utilize. This condition might be yet to be met by UMICs. However, the FDI-embodied foreign innovation in HICs might be different from LMICs, in which the technology transfer is less complicated. Besides, the fact that

HICs possess a relatively higher quality of governance, and a more stable business environment than LMICs and UMICs might also be a reason explaining a positive and significant FDI-embodied foreign innovation of HICs in this case.

In estimation for the full sample of all countries in model 4, estimated coefficients for high-skilled human capital are both positive and significant at 1% significance level. This result implies that high-skilled human capital is more important than skilled and unskilled human capital for the innovation capacity of all countries that obtained the level of middle-income and above.

In conclusion, the results highlight the importance of human capital for national innovation. Both skilled and high-skilled human capital plays a role in innovation capacity in MIEs, while unskilled human capital does not foster innovation. Skilled human capital is more vital for LMICs, while high-skilled human capital is required for UMICs and HICs. The three hypotheses are supported.

4.3 Robustness Checks

For robustness check, regressions are re-run under different modifications of panel data regressions. The relevance of fixed effect models is confirmed through the Hausman tests. The various modifications include the alternative measures of the human capital composition of average duration of schooling and an alternative measure of innovation capacity using both data on patent applications and utility models. The results confirm the robustness of the estimations in section 4.2.

4.3.1 No Control Variables

In the first set of robustness checks, only the main variables of human capital composition are included. The results of estimations in models 5, 6, and 7 presented in Table 6 confirm the robustness of the main results that are presented in section 4.2 (Models 1, 2, and 3).

For LMICs, the skilled-human capital proxied by tertiary education completion is the only significant variable (at 1%), with a positive coefficient. For UMICs and HICs, high-skilled human capital is confirmed to be significant (at 1%) to the innovation capacity of those groups. Their positive coefficients imply that the larger number of R&D personnel, the bigger contributions this group makes to aggregate innovation outcomes.

Table 4. Estimation models without control variables

Dependent variable: resident patent application (lnpat)	Model 5: Lower Middle-income	Model 6: Upper Middle-Income	Model 7: High-Income
Unskilled human capital (lnhc_usk)	0.518	0.008	-0.029
	(0.387)	(0.102)	(0.062)
Skilled-human capital (lnhc_sk)	**0.814*** **	-0.044	0.588
	(0.245)	(0.073)	(0.358)
High-skilled human capital (lnhc_hs)	0.128	**0.360*** **	**0.523*** **
	(0.142)	**(0.072)**	**(0.137)**
R&D capital (lnrd)	NA	NA	NA
FDI-embodied foreign innovation (lnfdi)	NA	NA	NA
Import-embodied foreign innovation (lnimp)	NA	NA	NA
Institutional quality (inst)	NA	NA	NA
Constant	-9.660	3.932	-3.482
	(3.677)	(1.512)	(4.776)
No. of observations	92	174	144
No. of groups	18	26	21
Wald chi2	37.27	130.52	74.23
Prob > chi2	0.000	0.000	0.000
R-squared (overall)	0.393	0.357	0.473
R-squared (within)	0.462	0.510	0.341
R-squared (between)	0.318	0.334	0.512
Country fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes

Note. Coefficients are reported with robust standard errors in parentheses. P-values: *p<0.10; **p<0.05; ***p<0.01.

4.3.2 Alternative Measures of Human Capital

The human capital composition can be constructed by the average years of schooling. In the second robustness check, skilled and unskilled human capital is measured based on the length of schooling in the Barro and Lee database. The educational variable for unskilled human capital is constructed based on the total length of primary and secondary education of the population over the age of 15. For skilled human capital, the total length of schooling until finishing tertiary education of the population over the age of 15 is counted.

Estimation results using alternative measures of human capital in Table 7 confirm that the main estimation results are robust. The signs of coefficients for human capital composition variables, and patent stocks for innovation capacity remain unchanged.

Table 5. Estimation models with alternative measures of human capital

Dependent variable: resident patent application (lnpat)	Model 8: Lower Middle-income	Model 9: Upper Middle-Income	Model 10: High-Income
Unskilled human capital (lnhc_usk)	-5.665	1.566	0.032
	(4.114)	(2.902)	(0.056)
Skilled-human capital (lnhc_sk)	**7.787****	-1.553	0.096
	(4.031)	(2.938)	(0.950)
High-skilled human capital (lnhc_hs)	-0.042	**0.235*****	**0.765*****
	(0.099)	**(0.089)**	**(0.199)**
R&D capital (lnrd)	0.343	0.298**	**0.208****
	(0.174)	(0.131)	**(0.091)**
FDI-embodied foreign innovation (lnfdi)	**0.385****	-0.016	0.111
	(0.157)	(0.079)	(0.094)
Import-embodied foreign innovation (lnimp)	-0.043	**0.330****	-0.066
	(0.204)	**(0.162)**	(0.109)
Institutional quality (inst)	0.178	-0.004	**0.257*****
	(0.282)	(0.067)	**(0.138)**
Constant	-0.746	1.727	-1.466
	(2.007)	(0.671)	(1.647)
No. of observations	82	150	128
No. of groups	16	26	20
Wald chi2	47.62	239.44	328.19
Prob > chi2	0.000	0.000	0.000
R-squared (overall)	0.532	0.355	0.681
R-squared (within)	0.413	0.615	0.723
R-squared (between)	0.676	0.270	0.702
Country fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes

Note. Coefficients are reported with robust standard errors in parentheses. P-values: *p<0.10; **p<0.05; ***p<0.01.

4.3.3 Alternative Measure of Innovation Capacity

In addition to patent application data, utility model applications data is added to reflect the innovation capacity in models 11, 12, and 13. Utility models are a form of patent-like protection for minor or incremental innovations. The rationale for utility models is tied closely to the patent system and its inability to extend legal rights to innovations or discoveries that fall short of the inventive step and/or novelty bars. The utility model applications data of each country for a given year are constructed by summing up all utility applications of resident inventors. The main estimation results shown in Table 8 confirm that the signs of coefficients for human capital composition variables, and innovation capacity remain unchanged.

Table 6. Estimation models with alternative measures of innovation capacity

Dependent variable: resident patent and utility models application (lnpu)	Model 11: Lower Middle-income	Model 12: Upper Middle-Income	Model 13: High-Income
Unskilled human capital (lnhc_usk)	0.077	-0.195	0.032
	(0.197)	(0.155)	(0.056)
Skilled-human capital (lnhc_sk)	**0.645****	0.040	0.096
	(0.257)	(0.073)	(0.950)
High-skilled human capital (lnhc_hs)	0.128	**0.432*****	**0.765*****
	(0.109)	**(0.142)**	**(0.199)**
R&D capital (lnrd)	0.506	0.251	**0.204***
	(0.191)	(0.180)	**(0.124)**
FDI-embodied foreign innovation (lnfdi)	**0.811*****	-0.027	0.111
	(0.136)	(0.145)	(0.094)
Import-embodied foreign innovation (lnimp)	-0.105	0.289	-0.066
	(0.258)	(0.183)	(0.109)
Institutional quality (inst)	-0.402	-0.055	**0.257****
	(0.200)	(0.086)	**(0.138)**
Constant	-6.717	-0.055	-1.466
	(3.372)	(0.088)	(1.647)
No. of observations	90	174	138
No. of groups	17	26	21
Wald chi2	184.94	294.02	328.19
Prob > chi2	0.000	0.000	0.000
R-squared (overall)	0.553	0.474	0.681
R-squared (within)	0.727	0.475	0.723
R-squared (between)	0.602	0.449	0.703
Country fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes

Note. Coefficients are reported with robust standard errors in parentheses. P-values: *p<0.10; **p<0.05; ***p<0.01.

5. Conclusion

Investment in human capital is paramount to speed up a country's development. Defining appropriate priority in human capital investment according to stages of development would facilitate the convergence journey more efficiently. Contributing to this topic, this study examines the role of human capital composition at a different level of skills to innovation at aggregate level of MIEs and above. The three categories of high-skilled human capital proxied through the number of R&D personnel, skilled human capital proxied through tertiary education, and unskilled human capital proxied through primary and secondary education are used to estimate the innovation-enhancing effect of the human capital composition. To the best of the author's knowledge, this is the first paper examining the impact of human capital composition on innovation at the aggregate level and the first paper using the combination of these three human capital variables. A panel of data of 65 countries covering three income levels of LMI, UMI, and high-income throughout 1985-2019 is used.

Results show that the innovation capacity enhancing effects of high-skilled human capital increase when countries reach UMI and HI levels. It implies that UMICs and above if concentrating on fostering the R&D personnel who are directly involved in the innovation process will be able to elevate the level of innovation capacity. UMICs, those that move closers to the technological frontier, should invest more to enlarge the pool of high-skilled R&D personnel. Imports of foreign technologies are found to be significant for UMICs. For high-income countries, the quality of institutions and foreign innovation spillover through FDI plays a vital role. R&D capital stocks are crucial for both UMICs and HICs.

For LMICs, the skilled level of human capital is found to be the most important part of the workforce that contributes to innovation capacity enhancement. By contrast, R&D personnel of high-skilled human capital is not contributing to the innovation capacity of LMICs. Given the assumption that innovation activities of LMICs are mainly from adopting foreign technological progress, this finding suggests that the larger pool of skilled-level workforce, the more positive results of innovation outcomes are yielded. LMICs should continue to invest in having a higher number of adults who complete tertiary education. Aside from human capital, the study also confirms the role of FDI-embodied innovation to strengthen the innovation capacity of LMICs.

Unskilled human capital is confirmed to not play an important role for both middle-income and high-income countries in fostering innovation capacity. However, obtaining the basic level of education of secondary education at the minimum would be the prerequisite for continuing study at higher levels.

Policies for the development of human capital for innovation if considering the importance of each level of human capital composition at each level of economic development might results in the more efficiently used of the limited resource.

Acknowledgments

The author is thankful to Professor Atsushi Kato, Gradudate School of Asia-Pacific Studies, Waseda University for his guidance and constructive comments on previous drafts of this paper.

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Notes

Note 1. Initial value of R&D stock is calculated as $R\&D_S = \frac{R\&D_{exp}}{(\delta + g)}$; R&D expenditure of the first year for which data of R&D expenditure are available is denoted as $R\&D^0_{exp}$; given average annual growth rate of the R&D expenditures g over the period for which published R&D data are available.

Note 2. Under this index, there are five areas of (1) size of government, (2) legal structure and property rights, (3) access to sound money, (4) freedom to trade internationally, and (5) regulation of credit, labor, and business.

Appendix A

List of countries in each income category

Lower Middle-Income Group	Upper Middle-Income Group	High Income Group
Bangladesh	Argentina	Chile
Cambodia	Armenia	Croatia
Ecuador	Azerbaijan	Czech Republic
Egypt, Arab Rep.	Belarus	Estonia
El Salvador	Brazil	Greece
Honduras	Bulgaria	Hong Kong
India	China	Hungary
Indonesia	Colombia	Ireland
Kyrgyzstan	Costa Rica	Israel
Lao PDR	Guatemala	Italy
Moldova	IR Iran	Japan
Mongolia	Kazakhstan	Korea, Republic of
Nepal	Malaysia	Mauritius
Pakistan	Mexico	Poland
Philippines	Panama	Portugal
Ukraine	Paraguay	Saudi Arabia
Uzbekistan	Peru	Singapore
Vietnam	Romania	Slovak Republic
	Russia	Slovenia
	Serbia	Spain
	South Africa	Taiwan
	Sri Lanka	
	Thailand	
	Tunisia	
	Turkey	
	Venezuela	

Note. The World Bank defines four income thresholds based on gross national income (GNI) per capita: low-income, lower than USD1,045; lower-middle income, USD1,046–USD4,045; upper middle-income, USD4,046–USD12,535; and high-income, greater than USD12,536 (World Bank, 2020).

Appendix B

Correlation matrix of variables in regressions of LMI group

	lnpat	lnhc_usk	lnhc_sk	lnhc_hs	lnrd	lnfdi	lnimp	inst
lnpat	1.000							
lnhc_usk	0.583	1.000						
lnhc_sk	0.287	0.506	1.000					
lnhc_hs	0.356	0.385	0.193	1.000				
lnrd	0.513	0.626	0.102	0.598	1.000			
lnfdi	0.388	0.524	0.314	0.078	0.512	1.000		
lnimp	0.238	0.405	0.375	0.071	0.356	0.768	1.000	
inst	0.302	0.243	0.107	0.241	0.081	0.025	-0.212	1.000

Appendix C

Correlation matrix of variables in regressions of UMI group

	lnpat	lnhc_usk	lnhc_sk	lnhc_hs	lnrd	lnfdi	lnimp	inst
lnpat	1.000							
lnhc_usk	-0.492	1.000						
lnhc_sk	0.269	-0.181	1.000					
lnhc_hs	0.624	-0.396	0.332	1.000				
lnrd	0.614	-0.210	0.337	0.570	1.000			
lnfdi	0.439	-0.210	0.283	0.356	0.433	1.000		
lnimp	0.206	0.147	0.397	0.275	0.248	0.392	1.000	
inst	0.245	-0.155	0.252	0.284	0.301	0.300	0.323	1.000

Appendix D

Correlation matrix of variables in regressions of HI group

	lnpat	lnhc_usk	lnhc_sk	lnhc_hs	lnrd	lnfdi	lnimp	inst
lnpat	1.000							
lnhc_usk	0.378	1.000						
lnhc_sk	0.139	0.618	1.000					
lnhc_hs	0.662	0.367	0.302	1.000				
lnrd	0.710	0.227	-0.079	0.681	1.000			
lnfdi	0.528	0.187	-0.147	0.419	0.560	1.000		
lnimp	0.239	0.196	-0.150	0.436	0.624	0.516	1.000	
inst	0.503	-0.005	-0.052	0.450	0.482	0.625	0.348	1.000

Appendix E

Correlation matrix of variables in regressions of all countries

	lnpat	lnhc_usk	lnhc_sk	lnhc_hs	lnrd	lnfdi	lnimp	inst
lnpat	1.000							
lnhc_usk	0.422	1.000						
lnhc_sk	0.319	0.182	1.000					
lnhc_hs	0.723	0.298	0.464	1.000				
lnrd	0.719	0.477	0.152	0.690	1.000			
lnfdi	0.639	0.331	0.392	0.551	0.623	1.000		
lnimp	0.500	0.455	0.078	0.443	0.683	0.578	1.000	
inst	0.643	0.381	0.422	0.606	0.584	0.586	0.439	1.000

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