Does Innovation Make Nations More Healthy? Evidence from Developing and Developed Countries

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Abstract

Our main contribution in this paper consists of analyzing long-run interactions between health status and innovation in the form of R&D activities accounting for possible economic development. For this purpose, we are based on a sample of fifteen developed and fifteen developing countries across the world during the period 2000–2017. As the principal interest is on the long-run effect, it is not essential to be concerned about the variable lags through which innovation will impact health. Therefore, to get the asymptotically efficient long-run impact of innovation on health, we have introduced both dynamic OLS and fully modified OLS for developed countries. Further, we have employed a technique based on panel ARDL methods for developing countries which deals with the stationary series problem of different orders to monitor possible association between population health and innovation in the long-run horizon. Our empirical results support long- and short-run causality running from R&D activities to health in all developed countries, whereas the just-mentioned causality prevails only in the long-run in case of developing countries. Finally, to check the robustness of the said association, we have implemented neural network-based NARX technique to validate the prediction of health status on the basis of R&D activities, and eventually, NARX supports our hypothesis in case of long-run through back-propagation. Policy recommendation includes the encouragement of more R&D activities and R&D-related policy implementation in both developed and developing nations to opt for better health status.

Keywords Health status · R&D investment · Panel Granger causality · Panel cointegration · Panel autoregressive distributed lag · NARX

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Introduction

The WHO secretariat had presented a document of information on intellectual property, public health, and innovation at the Fifty-sixth World Health Assembly in 2003. This noted that "...a significant proportion of the world's population, especially in developing countries, has yet to derive much benefit from innovations that are commonplace elsewhere. The reasons range from weak supply systems to unaffordable prices. The factors that drive innovation are often biased against conditions that disproportionately affect the populations of developing countries. ... Innovation to address conditions primarily affecting poor people is held back by a combination of market failure and underinvestment by the public sector. The process of bringing a new product to the market is both expensive and lengthy. Because of the resource implications and the uncertainties involved, creating an environment conducive to successful innovation is essential." (WHO, 2012).

In order to meet the health needs of the ever-increasing population of this World in the coming days, it's important to invest in Research and Development (R&D) now so that we can have the most effective solutions of the health problems.

R&D can best be described as transformation of a discovery or thought (idea) into a product which could address a health requirement. The end result should be a cost-effective, acceptable, accessible, and effective as well as safe health-related outcome to the people, especially to those who need it the most, that is, the poor people who cannot afford the costly health products. According to the definition of the Organisation for Economic Co-operation and Development (OECD) "Research and experimental development comprise creative work undertaken on a systematic base in order to increase the stock of knowledge, including knowledge about man, culture, and society, and the use of this knowledge to devise new applications" (OECD, 2001). Again, health R&D covers the areas of epidemiology, health services and health systems research, and health-related social research (OECD, 2001). Investment in R&D has become an important part to develop new health technologies or products for solving not only the long-lasting health challenges but also to improve the existing standard of health-services.

On one hand, we have witnessed rapid progress being made in the health sector worldwide over the last few decades, but, on the other hand, we have seen millions of people dying every year from various diseases or other health-related problems such as lack of infrastructural facilities. People in the developing and less-developed nations still die from infectious diseases or even from communicable diseases which cannot do any harm to the developed economies, since they have the access to the improved health products. Improvement of the global-health is impossible by the use of existing technologies only. The process of progress needs to go on with the invention of new health products which would benefit both developed and under-developed nations. We should recognize the fact that R&D in health comes with a multiplier effect. It saves lives, removes the cascading effects of various diseases, and thus improves the standard of living, saves

cost, and enhances productivity and growth of a nation. The developed nations also need improvements. In Europe also, chronic diseases along with emerging pandemic of new and old infectious diseases, demographic changes coupled with ever-increasing health costs are becoming challenging issues (Dabic & Peric, 2007). Analysis of demographic changes of Europe depicts that the European population falling in the age group of over 65 is expected to be doubled by 2050 (Dabic & Peric, 2007). In the USA, spending on health research development increased by 20.6% between 2013 and 2016. From developing nations, if we look at the two most populous nations, we will see that Chinese pharmaceutical R&D spending by Chinese firms rose over 4400 percent from \$163 million in 2000 to \$7.2 billion in 2016 (Lan et al., 2014). In India, this figure increased by 396% from \$480 million to \$1.9 billion during 2008–2016 (IBEF, 2017).

Health technologies can be described as those tools which prevent, diagnose, and cure diseases and improve health conditions. We must know that, for the devices to be improving the health conditions of the people, not only they should be cost-effective and affordable but also appropriate for the regions and communities in which they will be used in. So, R&D process needs to understand the health requirements of a nation or community, then go into the detailed research of existing diseases; then transforming ideas or inventions or even innovations into products; testing their safety, affordability, and cost-effectiveness for that nation; securing necessary approvals of the authority; and lastly, promoting the use of those health-related products and technologies in that nation.

But, the improvements in R&D do not come without any challenges. Since the market-incentive or profit for R&D is very low and especially in the developing nations, public investment becomes a necessity. But the ray of hope comes from the fact that spending on healthcare R&D is presently at 2nd place, following computing and electronics industries worldwide but the research from PricewaterhouseCoopers projects healthcare will take the top spot by 2020.¹ Healthcare saw a rise in their R&D spend from \$159 billion to \$169.5 billion from 2017 to 2018 (Lagasse, 2018). In 2019 the upward nature continued, for example, the USA saw an increase of 6.4% in R&D in healthcare in 2019, but from the end of 2019 due to the upsurge of COVID-19, there has been a sudden upsurge in the R&D in healthcare all over the world. Be it medical devices, or other aspects of healthcare, every single aspect of healthcare has seen an upsurge in R&D investment which ranges from at least 3.5% rise to more than 15% increase, it varies from one nation to another. What is important is that global R&D expenditure for pharmaceutical industry is estimated to be between US\$180 billion and US\$195 billion in 2022, but artificial intelligence (AI) spending in the healthcare and pharmaceutical industries is expected to increase from US\$463 million in 2019 to more than US\$2 billion by 2025 (ABI Research Report, 2020). So, we can say a lot has started to happen, as far as investment in R&D for health is concerned, but still, a lot needs to be done for the improvement of global health as disparities in several important health indicators still exist among nations, especially among developed and developing nations. There

¹ This result has been predicted based on figures taken from 1000 publicly listed R&D spenders (G-FINDER, 2013).

was a mismatch, identified in 1990, between the desired level of R&D in health care and actual level undertaken in reality. It was observed that below 10% of research expenditure on health was incurred by developed nations, but these nations then had witnessed above 90% of the world's burden of preventable mortality (Viergever, 2013). This is the famous 10/90 gap. The report on the commission on the health research for development which formed the basis for this famous 10/90 gap shows that, in developing nations, the potential years of life lost was 93%, whereas in the developed nations it was only 7%. Again, developed nations made 95% of health research expenditures by purpose, but developing nations made only 5%. In 1986, it was estimated that the investment in R&D in healthcare was around 30 billion USD and it increased to 240 USD in 2010 (Rottingen et al., 2013), but post-1990 has seen an upsurge in investment in R&D in healthcare from the third world developing nations as well, including China, India, and Brazil. Now, China and the USA have been competing for the first two spots, as far as investment in R&D is concerned in healthcare along with several other developing nations in the list of top 10 or top 15 nations, which could not be seen before 1990. Hence, a lot of developing nations, including India and other Asian nations, African nations, etc. need to increase investment in R&D for healthcare.

If one goes through the existing works in this sphere, one would find that they are largely based on finding the causes of high or low values of health indicators, such as infant mortality rate (IMR) and life expectancy at birth (LE) at different parts of the world and recommending policies to further improves such scenarios. These papers have emphasized on the roles of both R&D and government intervention as their policy recommendations. Few papers have considered R&D in health as an important aspect. Their works are largely based on finding whether investment in R&D of health is profitable or not, why private sector companies are less willing to invest in R&D of health, and what should be done to improve the existing condition of that, whether investment in R&D of health is significant, etc. But, none of the papers has considered both short-run and long-run impacts of R&D investment and its related variables, namely, proportion of GDP spent for R&D, number of people involved in R&D, patents by both residents and nonresidents, on the health status of a nation or on IMR and LE of a nation. This paper looks to fill up that lacuna by its short-run and long-run analysis using panel regression for 15 developed and 15 developing nations² and goes on to estimate the long-run impact of R&D investment on health status by considering dynamic ordinary least square (DOLS), fully modified OLS (FMOLS) techniques (for developed nations), and auto-regressive distributed lag model (for developing nations). We have also considered neural network methods for the purpose of accurate forecasting, which has not been done till date to the best of our knowledge, for the purpose of forecasting about health status

² The 15 developed nations we have considered are Norway, Australia, Switzerland, Netherlands, USA, Germany, New Zealand, Canada, Singapore, Denmark, UK, France, Russia, Sweden and Japan. The 15 developing nations we have considered are Argentina, Brazil, China, Chile, India, Israel, Malaysia, Taiwan, Mexico, South Africa, Nigeria, Qatar, South Korea, Bangladesh, and Saudi Arabia. The selection of these nations are mainly based on ranking in HDI over the last decade or so.

based on innovations. Application of so many aspects together, for both developed and developing nations, considering both short-run and long-run, is almost absent in the field of work in health sector. This is the main motivation behind this paper.

A Review of Existing Literature

There have been quite a few works that depict the impact of research and development on economic growth or on any specific sector of an economy, but the number of works involving health with research and development has been very few. Here, we shall discuss, in brief, the works that have incorporated R&D along with health. But first, we shall make a brief discussion about papers that have emphasized on different health indicators because that would help us to understand the need of investment in R&D of health sector.

Reidpath and Allotey (2003) have shown, in their study, to consider IMR as an important health indicator by showing strong correlation, 0.91 to be exact, between IMR and DALE for 180 nations by using 1997 World Bank and WHO data and thus rejected the criticism of using IMR as a health indicator. Sartorius and Sartorius (2014) have used IMR data for the period of 1990–2011 for 192 nations and have used spatial clustering for identifying significant higher risk IMR nations. They have quantified risk factors and associated decomposition values by using a robust ecological generalized linear negative binomial regression model. They have observed a reduction in IMR in most of the nations except in Sub-Saharan African nations and parts of Asian nations. They have identified HIV (for African nations), MMR, and lack of basic needs such as sanitation, water, and female education as prominent determinants of high IMR. They have found MMR has the highest impact on IMR, so they have urged for proper measures in order to achieve millennium development goal number 4. Mukherjee et al. (2019) have made an ecological study about the determinants of IMR in rural India. They have used state-level values of IMR, obtained from Sample Registration System, 2015, as dependent variable and state-level literacy rate in females, unemployment rates of females, GINI index, and round-the-clock neonatal services in primary health centers in the rural areas and the per capita gross state domestic product at purchasing power parity (GSDP at PPP) of the states as the influencing variables on IMR. They have used bivariate and multivariate linear regression methodology and took the help of Pearson's correlation coefficient. They have found rural female literacy rate has the most significant impact on rural IMR, but the authors are of the view that all the determinants should be given proper attention. Bohm et al. (2017) in their work have considered R&D-driven health progress and access to healthcare by setting up a model of gerontological founded human aging which overlaps generations. Their work, as expected, has established a positive relation between human longevity and increasing share of GDP being invested in health. The astonishing outcome of the work is that if the share of GDP invested in health is frozen at 2020 level along with rationing access to healthcare services; it would cause a substantial reduction in the life expectancy in the long run, especially to the young generation.

Viergever (2013) feels that the investment in R&D is generally undertaken by the profit-seeking private sectors, and the lack of enough support by the public sector or government coupled with very minimum profit for the private sector has resulted in such a mismatch, and thus, this process has resulted in negligence of certain health-related products, certain population. He has tried to provide an overview of this problem along with its solutions, which he feels mainly lies in the CEWG report of 2012.³ Dabic and Peric (2008), in their work on Croatia, have raised a question if there exists any impact of R&D investment on healthcare system or not. They have used the available secondary data from various sources on the Croatian economy and analyzed that there has been substantial increase in investment on R&D of health sector; both from national and international sources and importance on research projects have been emphasized, and the authors feel that such projects, in the long run, would improve the health quality and health sector of the Croatian economy. Jorring et al. (2017), in their work, have argued that investment in R&D of health is a risky affair for the firms conducting such research. By using financial instruments, Food and Drug Administration (FDA) hedges, historical FDA approval data, they have shown that, by allowing better risk-sharing between investors in R&D of health and capital markets more generally, FDA hedges could minimize such risks and encourage health innovations and its outcomes. Karpa and Nowakowski (2018) have made an evaluation, based on empirical data, of R&D returns in healthcare sector for a number of leading companies involved in this function. They have used the parametric production function setting and finite distributed lag model. Their work finds a positive correlation between impacts of investment in R&D on product sales, although the magnitude of such relation is falling. So, they have suggested public participation, or even public–private co-operation to sustain such innovations.

The paper is organized in the following manner. “Theoretical Background” illustrates the theoretical background of our study. “Data and Methodology” describes about the data and methodology used in the paper. “Results and Discussions” discusses about the results of our study; “Health Forecast and Innovation” is used for the purpose of health forecast and innovations, from the neural network method; and finally, concluding remarks are made in “Concluding Remarks and Policy Implications.”

Theoretical Background

Health, Production, and Innovation

Let us start with the sagacity that the R&D augmented health sector always emphasizes more on innovation by making new design or making a variation of the existing one. Such innovation gives enough space to the R&D augmented health sector to enjoy more monopoly power in the market. Furthermore, the R&D augmented health

³ The Consultative Expert Working Group on Research and Development: Financing and Coordination (CEWG).

sector produces a horizontally differentiated good, that is, good H , under the assumption of increasing returns to scale (IRS) (Krugman, 1979, 1980). To produce good H , the R&D sector has to employ skilled labor with capital. To be more specific, here, we assume that fixed amount of health-specific skilled labor (η) is required to make innovation, and the same innovation also needs β units of R&D capital per unit of production or β units of R&D investment per unit of output (Das & Chatterjee, 2020). Given the aforesaid arrangement along with free entry and monopolistic competition give us the liberty to demonstrate the following price equals to average cost expression for a representative R&D augmented health firm (i):

$$P_{H_i} = \eta(W_H/H_i) + \beta R_{R\&D} \quad (1)$$

where, P_{H_i} is the price of the innovation innovated by the i th R&D augmented health firm; W_H and $R_{R\&D}$ are the rate of return to the skill labor and R&D capital, respectively.

From the equality between marginal cost and marginal revenue, we get the following equilibrium condition for the i th R&D augmented health

$$P_{H_i} = (E_i/E_i - 1)\beta R_{R\&D} \quad (2)$$

where, E_i is the price elasticity of demand for the innovation produced by the i th health firm.

Using Eqs. (1) and (2), we find the following expressions

$$\hat{P}_{H_i} P_{H_i} = (\eta W_H/H_i) \hat{W}_H - (\eta W_H/H_i) \hat{H}_i + (\beta r) \hat{R}_{R\&D} \quad (3)$$

$$\hat{P}_{H_i} P_{H_i} = \{[E_i/(E_i - 1)]\beta R_{R\&D}\} \hat{R}_{R\&D} \quad (4)$$

Using (3) and (4) one can obtain

$$\{1/(E_i - 1)\}\beta R_{R\&D}\} \hat{R}_{R\&D} = (\eta W_H/H_i) \hat{W}_H + (\eta W_H/H_i) \hat{H}_i \quad (5)$$

Following Das and Chatterjee (2020) and by assuming $\hat{W}_S = 0$, we get the Eq. (5) in the following form

$$\{1/(E_i - 1)\}\beta R_{R\&D}\} \hat{R}_{R\&D} = (\eta W_H/H_i) \hat{H}_i \quad (6)$$

Equation (6) can be rewritten as

$$\hat{H}_i = [\{(1/(E_i - 1))\beta R_{R\&D}\}/(\eta W_H/H_i)] \hat{R}_{R\&D} \quad (7)$$

Equation (6.1) illustrates the positive relationship between health and investment in R&D, as $\{(1/(E_i - 1))\beta R_{R\&D}\}/(\eta W_H/H_i) > 0$. More precisely, we get the following

$$H = f(R_{R\&D}); f' > 0 \quad (8)$$

The health status at each moment is proportional to R&D investment in health sector, i.e.,

$$H = \psi R_{R\&D}; 0 < \psi < 1 \quad (8).$$

Health and Innovation in the Long Run

Health status is generated directly with investment in a given level of innovation at a given time. However, over time, a nation moves towards innovation in a continuous matter. Again, investment in R&D along with human capital explains innovation. Hence, stock of capital and R&D expenditure jointly determine health status of a nation (H), in long run. Thus, from Eq. (8), the long-run specification can be drawn as

$$\ln H = \ln \psi + \ln R_{R\&D} \quad (9)$$

Specification (9) gives us the steady-state relationship between the variables of our interest as

$$\dot{H}/H = \dot{\psi}/\psi + \dot{R}_{R\&D}/R_{R\&D} \quad (10)$$

Here, we further assume that the health per unit of R&D expenditure (ψ) is changing over time as

$$\psi = \psi_0 e^{\theta t} \quad (11)$$

Using specification (11), the new steady-state relationship can be expressed as

$$\frac{\dot{H}}{H} = \theta + \frac{\dot{R}_{R\&D}}{R_{R\&D}} \quad (12)$$

Equation (12) reveals that in long-run improvement in health status enhances with an improvement in R&D to health. The rest of the paper is trying to verify its empirical validity using panels of both developed and developing economies.

Data and Methodology

We have used annual data for fifteen developed and fifteen developing countries across the world during the period 2001–2017. The main source of our data is the World Development indicators (hereafter, WDI). Here, the main focuses of this study are to examine both short-run dynamics and long-run association between health status and R&D activities in major developed and developing countries. To describe the health status for developed and developing economies, we use life expectancy at birth (LE) and infant mortality rate (IMR) as two most suitable health indicators. Life expectancy at birth indicates the number of years a newborn infant would live if prevailing patterns of mortality at the time of its birth were to stay the same throughout its life. Life expectancy is the most widely used measure of population health care and has also several advantages over other indicators of health status, including the following: (i) it depends on both infant mortality and other

Table 1 Descriptive statistics of variables

Variable	Mean	Min	Max	St. Dev	Skewness	Kurtosis
Panel: developed countries						
LE	80.43	76.63	84.09	1.85	-0.123	2.12
IMR	4.42	1.90	7.10	1.38	0.043	2.17
RDGDP	2.29	1.54	3.40	0.57	0.40	1.83
RDP	4201.44	2886.68	5332.61	638.33	0.08	2.32
PR	118,281.5	3929.00	384,201.0	135,923.5	0.63	1.69
PNR	63,842.67	1593.00	310,244.0	84,787.32	1.65	4.49
Panel: developing countries						
LE	68.56	53.44	77.28	7.16	-0.936	2.54
IMR	27.17	6.70	66.60	13.90	0.682	2.79
RDGDP	1.05	0.04	2.12	0.48	0.380	3.26
RDP	608.58	89.19	2003.97	362.70	1.169	5.15
PR	127,819.4	15.00	1,245,709.0	294,073.5	2.660	9.15
PNR	37,044.68	1738.00	135,885.0	42,198.39	1.237	3.02

Source: computed by the authors

mortality rates, thus incorporating mortality rates at all stages in life; (ii) it is not biased by age structure; and (iii) data on life expectancy at birth are available for a reasonably large number of countries and time periods (Herzer & Nunnenkamp, 2015). However, the use of life expectancy as an indicator of health has been criticized on the following grounds: (i) longer life expectancy does not necessarily translate into better health and (ii) second limitation is that average life expectancy does not reveal the variation of health conditions within countries. To overlook these, we have also used the infant mortality rate (hereafter, IMR) as the second-best measure of population health status for developing economies in our question. Again, we take the R&D expenditure as percentage of GDP (RDGDP) as our independent variable since we aim to access to the level of health scenario of countries in terms of health status taking into account R&D activities. For the choice of the variables introduced as explanatory determinants of potential population health status, apart from RDGDP, we use patents by nonresidents (PNR), patents by residents (PR), and persons' presence in R&D (RDP) to capture the effectiveness of R&D activities in developing and developed countries. Data descriptions and resources are presented in Table 1.

Model Specification

To check the association between health status and R&D activities for the two panels, here, we have constructed the following bi-variate model of the form

$$Health_{it} = \alpha_i + \delta_i t + \beta RDGDP_{it} + \varepsilon_{it} \quad (13)$$

To find out the potential presence of PNR, PR, and RDP (along with RDGDP) on health of a particular nation and also to examine the robustness of the model under nonlinearity, we estimate the following equations

$$Health_{it} = \alpha_i + \delta_i t + \beta RDGDP_{it} + \gamma RDGDP_{it} * RDP_{it} + \varepsilon_{it} \quad (14)$$

$$Health_{it} = \alpha_i + \delta_i t + \beta RDGDP_{it} + \gamma RDGDP_{it} * PR_{it} + \varepsilon_{it} \quad (15)$$

$$Health_{it} = \alpha_i + \delta_i t + \beta RDGDP_{it} + \gamma RDGDP_{it} * PNR_{it} + \varepsilon_{it} \quad (16)$$

where, α_i , are country fixed effects, $\delta_i t$ are country-specific time trends, $Health_{it}$ is refer to the health status of cross-section i 's population in time t .

Traditional Econometric Methods

In this study, we have considered two panels, one for developed countries and the other is for developing nations. As we are specifically interested to check the inherent long-run dependency of health status on the respective nation's R&D-related activities, we start our investigations with panel unit root tests. To serve this purpose, we use LLC test (Levin et al., 2002), IPS test (Im & Pesaran, 2003), PP-Fisher chi-square (Maddala & Wu, 1999), and Fisher-type ADF test, where LLC test is performed under the assumption of homogeneity of coefficients across cross-sections, and the rest of the panel unit root tests are performed by assuming heterogeneous coefficients across different cross-sections. The usual convention of drawing outcomes from panel unit root test is to check that whether panel cointegration can be performed to the corresponding panel or not. If panel unit root tests suggest that all the variables of our concern are integrated of order one, that is, $I(1)$, we can easily run the panel cointegration tests. However, if the tests reveal different order of integration among variables, that is, some of the variables follow $I(0)$ and others follow $I(1)$ then panel ARDL method can be used.

The panel of developed countries owing to panel unit root tests (as described in Table 2) suggests that all the variables follow $I(1)$. In order to test for cointegration, we use the standard panel and group test statistics suggested by Pedroni (1999, 2004). Pedroni (1999, 2004) proposes seven statistics to test the null hypothesis of no cointegration in heterogeneous panels. These tests include two types of tests. The first is the cointegration tests panel (within-dimension). Within tests, dimensions consist using four statistics, namely, panel ν -statistic, panel ρ -statistic, panel PP-statistic, and panel ADF-statistic. These statistics pool the autoregressive coefficients across different members for the unit root tests on the estimated residues, and the last three test statistics are based on the “between” dimension (the “group”). These tests are group ρ , group PP-statistic, and group ADF-statistic. A potential problem with the Pedroni approach is that it does not allow for cross-sectional dependence. To test for cointegration in the presence of possible cross-sectional dependence, we also used the error correction model (ECM) for cointegration tests recently developed by Gengenbach et al. (2008). Following the common correlated effects (CCE) approach, this test involves estimating separate

Table 2 Panel unit root tests for developed countries

Variable	At level				At first difference			
	LLC test	IPS test	ADF test	PP test	LLC test	IPS test	ADF test	PP test
LE	−0.94 (0.17)	1.82 (0.96)	10.39 (0.40)	7.25 (0.75)	−5.94 (0.04)	−1.34 (0.08)	37.50 (0.00)	52.54 (0.00)
IMR	−0.91 (0.17)	1.87 (0.95)	10.53 (0.40)	12.55 (0.41)	−4.60 (0.00)	−3.96 (0.00)	35.57 (0.00)	52.54 (0.00)
PNR	−0.69 (0.24)	−0.12 (0.44)	8.87 (0.54)	9.32 (0.87)	−3.72 (0.00)	−1.30 (0.09)	29.23 (0.00)	24.60 (0.00)
PR	−0.83 (0.36)	0.22 (0.58)	6.67 (0.75)	7.78 (0.65)	−6.76 (0.00)	−5.80 (0.00)	48.72 (0.00)	47.65 (0.00)
RDGDP	1.14 (0.87)	1.22 (0.88)	6.15 (0.80)	6.84 (0.73)	−7.41 (0.00)	−6.43 (0.00)	52.23 (0.00)	55.93 (0.00)
RDP	−0.17 (0.42)	−0.86 (0.19)	14.18 (0.16)	15.01 (0.84)	−6.40 (0.00)	−5.76 (0.00)	47.39 (0.00)	70.53 (0.00)

This table reports the test statistic followed by the probability values in parentheses for the three tests performed in the four tests performed in ascertaining the stationarity of the variables.

conditional ECMs for each country using the cross-section averages of the endogenous and exogenous variables. Gengenbach et al. (2008) propose the following test statistic to test the null hypothesis of no cointegration: the average Wald chi-square test statistic of the hypothesis that all coefficients of the lagged levels are zero.

After confirmation of the existence of a cointegration relationship between the series, it must be followed by the estimation of the long-term relationship. There are different estimators available to estimate a vector cointegration panel data, including with and between groups such as OLS estimates, FMOLS estimators, and estimators DOLS. As shown by Wagner and Hlouskova (2010), the panel DOLS estimator outperforms other asymptotically efficient panel cointegration estimators. Consequently, DOLS estimator is more efficient estimator, though we report the estimation outcomes of both FMOLS and DOLS to judge the robustness of our study. The DOLS regression can be represented as (in an extended specification of Eq. (13)) (Kao & Chiang, 2000).

$$Health_{i,t} = \alpha_i + \partial_i t + \beta RDGDP_{i,t} + \sum_{j=-k}^k \theta_{ij} \Delta RDGDP_{i,t-j} + \varepsilon_{i,t} \quad (17)$$

where Δ is the difference operator, and k is the number of leads and lags.

Again, the panel of developing countries owing to panel unit root tests (as described in Table 3) suggests that health-related variables follow $I(0)$, and R&D-related variables follow $I(1)$. Under such circumstances, we referred largely to the technique introduced by Pesaran et al. (1999, 2004). Indeed, panel data methods based on dynamic panel heterogeneity are quite helpful to get efficient estimators. In fact, here we employ panel ARDL methods to produce consistent and efficient estimators of the parameters in the presence of country heterogeneity in contrast with previous studies based on variables integrated with the same order. To address the

Table 3 Panel unit root tests for developing countries

Variable	At level				At first difference			
	LLC test	IPS test	ADF test	PP test	LLC test	IPS test	ADF test	PP test
LE	− 8.94 (0.00)	− 10.33 (0.00)	137.61 (0.00)	34.07 (0.00)	-	-	-	-
IMR	− 2.72 (0.00)	− 4.31 (0.00)	44.15 (0.00)	176.09 (0.00)	-	-	-	-
PNR	− 0.69 (0.24)	− 0.17 (0.42)	8.10 (0.61)	10.32 (0.77)	− 1.88 (0.02)	− 2.45 (0.00)	22.91 (0.01)	54.85 (0.00)
PR	4.40 (1.00)	8.26 (1.00)	1.61 (0.99)	1.32 (0.99)	− 4.76 (0.00)	− 1.46 (0.07)	34.70 (0.00)	43.90 (0.00)
RDGDP	− 0.99 (0.15)	0.68 (0.75)	4.43 (0.81)	4.35 (0.82)	− 3.37 (0.00)	− 3.12 (0.00)	25.02 (0.00)	26.99 (0.00)
RDP	3.51 (0.99)	3.94 (1.00)	0.93 (0.98)	1.49 (0.95)	− 8.92 (0.00)	− 6.25 (0.00)	33.64 (0.00)	34.68 (0.00)

This table reports the test statistic followed by the probability values in parentheses for the three tests performed in the four tests performed in ascertaining the stationarity of the variables

drawbacks of the models presented for the panel of developed countries, we consider the following ARDL (p, q) model based on the specification of Pesaran et al. (1999) and by extending Eq. (13):

$$Health_{it} = \alpha_i + \lambda_t + \sum_{j=1}^k \gamma_j Health_{i,t-j} + \sum_{j=1}^k \beta_j RDGDP_{i,t-j} + \varepsilon_{it} \quad (18)$$

where $Health_{it}$ and $RDGDP_{it}$ stand for the measures of health and RDGDP, α_i are country-specific fixed effects, and λ_t represents time dummies.

Neural Network Methods

Nonlinear autoregressive models with exogenous input (NARX) neural network are a variant of recurrent network (Lin et al., 1996, Gao & Meng, 2005) that has been successfully utilized in time series prediction problems. Contrary to the conventional econometric methods, NARX on the contrary can efficiently be used for modeling nonstationary and nonlinear time series for forecasting. Mathematically, input–output representation of nonlinear discrete time series in NARX network is specified as

$$Health(n+1) = f[health(n); Rdgdp(n)] \quad (19)$$

where $health(n)$ and $RRDGDP(n)$ are the sample value of the time series at time n . In order to use the full computational abilities of the NARX network for nonlinear time series prediction, we use the following mechanism (Xie, Tang & Liao, 2009);

$$RDGDP(n) = x_1(n) = [RDGDP(n), RDGDP(n - \tau), \dots, RDGDP(n - (d_E - 1)\tau)] \quad (20)$$

where, τ , is the embedding delay, and d_E is the embedding dimension and we set $d_{RDGDP} = d_E$.

It is to be noted that there are two modes which have a concern in training NARX network. The first one is called parallel (P) mode and the other one is called series–parallel (SP) mode. Output signal corresponding to each mode can be expressed as

$$Health_{sp}(n) = [RDGDP(n), \dots, RDGDP(n - (d_E - 1)\tau)] \quad (21)$$

$$Health_p(n) = [RDGDP(n), \dots, RDGDP(n - (d_E - 1)\tau)] \quad (22)$$

Therefore, the NARX networks implement the following predictive mappings:

$$Health\hat{h}(n + 1) = \hat{f}[Health_{sp}(n), RDGDP(n)] = \hat{f}[Health_{sp}(n), x_1(n)] \quad (23)$$

$$Health\hat{h}(n + 1) = \hat{f}[Health_p(n), RDGDP(n)] = \hat{f}[Health_p(n), x_1(n)] \quad (24)$$

where the nonlinear function $\hat{f}(\cdot)$ is readily implemented through a multilayer perceptron trained with the usual NN backpropagation algorithm.

Results and Discussions

Health Status and R&D Activities in Developed Countries

As both the two series are $I(1)$, we can go for testing cointegration between the variables to find long-run association between health and R&D. Panel cointegration test requires estimating Eq. (13). First, we try to run the cointegration tests between LE and RDGDP, and thereafter, we run the same test for IMR and RDGDP. The results for Pedroni test at different specifications are given in Tables 4 and 5. The Pedroni test depicts the two series to be cointegrated in a maximum of the alternatives justifying the existence of long-run equilibrium relations between R&D and LE, and R&D and IMR.

Since the variables are in long-run associations for the study period, we examined the vector error correction to see the dynamics after deviations (if any) from the equilibrium relations. The results are shown in Table 6. It is observed that the EC term for the health status in terms of LE and IMR being the dependent variables are of desired negative signs and statistically significant, but the result for R&D as the dependent variable is not statistically significant, although they follow desired sign in case where IMR is treated as independent variable. This leads us to conclude that the errors are corrected in the case when health (either in terms of LE or IMR) is the dependent variable, and further, it shows that there is long-run causal effect from R&D to health. The test for short-run interplays in the panel by means of Wald test

Table 4 Pedroni residual panel cointegration test for R&D share and LE

Hypotheses → / test criteria ↓	Null hypothesis: <i>no cointegration</i>	Statistic (Prob)	Weighted statistic (Prob)
No deterministic trend	Alternative hypothesis: common AR coefficients (within-dimension)	Panel v-statistic	0.37 (0.36)
		Panel rho-statistic	− 7.14 (0.00)
		Panel PP-statistic	− 7.07 (0.00)
		Panel ADF-statistic	− 6.27 (0.00)
	Alternative hypothesis: individual AR coefficients (between-dimension)	Group rho-statistic	− 2.31 (0.01)
		Group PP-statistic	− 5.78 (0.00)
		Group ADF-statistic	− 6.23 (0.00)
		Panel v-statistic	− 2.81 (0.99)
		Panel rho-statistic	− 4.71 (0.00)
Deterministic intercept and trend	Alternative hypothesis: common AR coefficients (within-dimension)	Panel PP-statistic	− 7.53 (0.00)
		Panel ADF-statistic	− 4.31 (0.00)
		Group rho-statistic	− 0.54 (0.30)
		Group PP-statistic	− 5.37 (0.00)
	Alternative hypothesis: individual AR coefficients (between-dimension)	Group ADF-statistic	− 5.63 (0.00)
		Panel v-statistic	2.32 (0.01)
		Panel rho-statistic	− 7.39 (0.00)
		Panel PP-statistic	− 6.44 (0.00)
		Panel ADF-statistic	− 5.18 (0.00)
No deterministic intercept and trend	Alternative hypothesis: common AR coefficients (within-dimension)	Group rho-statistic	− 2.47 (0.01)
		Group PP-statistic	− 5.35 (0.00)
		Group ADF-statistic	− 5.18 (0.00)
	Alternative hypothesis: individual AR coefficients (between-dimension)	Panel v-statistic	0.15 (0.48)
		Panel rho-statistic	− 3.85 (0.00)
		Panel PP-statistic	− 4.07 (0.00)
		Panel ADF-statistic	− 2.52 (0.01)
		Group rho-statistic	−
		Group PP-statistic	−
		Group ADF-statistic	−

Source: computed by the authors

Table 5 Pedroni residual panel cointegration test for R&D share and IMR

Hypotheses → / test criteria ↓	Null hypothesis: <i>no cointegration</i>	Statistic (Prob)	Weighted statistic (Prob)
No deterministic trend	Alternative hypothesis: common AR coefficients (within-dimension)	Panel v-statistic	0.24 (0.39)
		Panel rho-statistic	– 7.34 (0.00)
		Panel PP-statistic	– 7.89 (0.00)
		Panel ADF-statistic	– 5.67 (0.00)
	Alternative hypothesis: individual AR coefficients (between-dimension)	Group rho-statistic	– 2.41 (0.01)
		Group PP-statistic	– 5.78 (0.00)
		Group ADF-statistic	– 6.19 (0.00)
Deterministic intercept and trend	Alternative hypothesis: common AR coefficients (within-dimension)	Panel v-statistic	– 2.21 (0.99)
		Panel rho-statistic	– 4.71 (0.00)
		Panel PP-statistic	– 6.72 (0.00)
		Panel ADF-statistic	– 5.31 (0.00)
	Alternative hypothesis: individual AR coefficients (between-dimension)	Group rho-statistic	– 0.51 (0.30)
		Group PP-statistic	– 5.71 (0.00)
		Group ADF-statistic	– 5.36 (0.00)
No deterministic intercept and trend	Alternative hypothesis: common AR coefficients (within-dimension)	Panel v-statistic	2.28 (0.01)
		Panel rho-statistic	– 7.39 (0.00)
		Panel PP-statistic	– 6.36 (0.00)
		Panel ADF-statistic	– 5.28 (0.00)
	Alternative hypothesis: individual AR coefficients (between-dimension)	Group rho-statistic	– 3.18 (0.01)
		Group PP-statistic	– 5.75 (0.00)
		Group ADF-statistic	– 4.98 (0.00)

Source: computed by the authors

Table 6 VECM results for LE and IMR

Dependent variables	EC terms	Probability	Whether errors corrected	Remarks
$D(LE)$	$C(1) = -0.06$	0.00	Yes	Long-run causality from RDGDP to LE
$D(RDGDP)$	$C(1) = 0.38$	0.52	No	No long-run causality from LE to RDGDP
$D(IMR)$	$C(1) = -0.18$	0.00	Yes	Long-run causality from RDGDP to IMR
$D(RDGDP)$	$C(1) = -0.32$	0.35	No	No long-run causality from LE to RDGDP

Optimum lag has been derived as 2

shows that there are significant bilateral causal relations from all the past values of health measures (LE or IMR) and R&D measure (RDGDP) to LE (or IMR) and the outcomes are displayed in Table 7.

Therefore, the panel data results of developed countries unambiguously establish that RDGDP and LE (or IMR) are cointegrated, and there are one-way causal relations between the two variables, that is, the causality running from health status to R&D activities. The robustness of our outcomes is also verified by employing panel Granger causality tests both with common coefficients and individual coefficients, and the results are depicted in Tables 8 and 9. Hence, the developed countries are requiring more innovation in terms of R&D activities to promote health status.

To get the long-run coefficients of the above stated probable long-run associations, we use DOLS, and for further verification, we employ FMOLS also. Tables 10 and 11 depict the outcomes of DOLS and FMOLS techniques for dependent variables like LE and IMR, respectively.

Table 7 Short-run causality through Wald test

Dependent variable	Chi-square	Prob	Remarks
$D(LE)$	7.85	0.00	All past values of LE and RDGDP $\rightarrow$ LE of the current period
$D(RDGDP)$	3.60	0.05	All past values of RDGDP and LE $\rightarrow$ RDGDP of the current period
$D(IMR)$	14.45	0.00	All past values of IMR and RDGDP $\rightarrow$ IMR of the current period
$D(RDGDP)$	8.40	0.00	All past values of RDGDP and IMR $\rightarrow$ RDGDP of the current period

Source: computed by the authors

Table 8 Panel Granger causality tests (common coefficients) for developed countries

Null hypothesis	Lags	<i>F</i> statistic	Prob. values
RDGDP does not Granger cause LE	6	4.427	0.001
LE does not Granger cause RDGDP	6	1.418	0.227
RDGDP does not Granger cause IMR	6	2.160	0.063
IMR does not Granger cause RDGDP	3	0.896	0.505

Source: author's calculation

Columns (1) and (5) of Tables 10 and 11 illustrate positive impact of RDGDP on health status in developed countries. The estimated coefficients are positive and significant at the 5% level. It shows that RDGDP is responsible for about 2.99 to 3.77 basis increase in life expectancy, while such innovation explains 1.74 to 2.00 basis fall in infant mortality in developed economies. It seems that the aspect of innovation is multidimensional, and hence, it cannot be captured only by RDGDP. Therefore, we have incorporated three additional R&D-related variables, for example, RDP, PR, and PNR. To make the matter more quantitative, we accommodate these variables with RDGDP by means of three interaction terms and they are RDGDPRDP, RDGDPPR, and RDGDPPNR. Columns (2) and (6) of Tables 10 and 11 illustrate the significant impact of both RDGDP and the presence of RDP with RDGDP on health status in developed countries. Similarly, columns (3) and (7) and columns (4) and (8) of Tables 10 and 11 illustrate the significant outcomes of RDGDPPR and RDGDPPNR, respectively, on health of developed countries. These results further reveal three threshold values of the additional three R&D-related indicators as RDP*, PR*, and PNR* for which a positive impact of RDGDP can be found within multidimensional innovation or R&D set up. From these tables, we derive the threshold values and they are as follows: RDP* can take a value within the range of 2365 to 2760, PR* varies within the range of 195 to 317, and PNR* should take the value in between 40 and 61.

Health Status and R&D Activities in Developing Countries

The panel of developing countries reflects (Table 3) that health variables and R&D-related variables are integrated in different orders. In fact, health indicators like LE and IMR follow $I(0)$, whereas variables like RDP, PR, and PNR follow $I(1)$. Under such backdrop

Table 9 Panel Granger causality tests (individual coefficients) or Dumitrescu-Hurlin panel causality tests for developed countries

Null hypothesis	Lags	W-Stat	Zbar-stat	Prob. values
RDGDP does not homogenously cause LE	2	8.755	2.170	0.030
LE does not homogenously cause RDGDP	3	4.046	0.021	0.982
RDGDP does not homogenously cause IMR	3	7.959	1.807	0.070
IMR does not homogenously cause RDGDP	3	2.376	−0.741	0.458

Source: author's calculation

Table 10 Estimates of the long-run effect of R&D on LE in developed countries

Independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RDGDP	2.99* (2.80)	-4.73* (-2.14)	1.90* (48.59)	1.75** (2.11)	3.77** (1.92)	-2.76*** (-1.82)	3.70*** (1.85)	0.49*** (1.99)
RDGDPRDP		0.002* (11.50)				0.01* (3.95)		
RDGDPPR			-0.006* (-7.04)				0.023 (0.11)	
RDGDPPNR				0.029* (2.61)				0.035*** (2.12)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DOLS	No	No	No	No	Yes	Yes	Yes	Yes
FMOLS	Yes	Yes	Yes	Yes	No	No	No	No
Sample period	2001–2017	2001–2017	2001–2017	2001–2017	2002–2016	2002–2016	2002–2016	2002–2016
Countries	15	15	15	15	15	15	15	15
Observations	239	239	239	239	215	215	215	215

The dependent variable is LE, and *t*-statistics are in parenthesis

*** (**) [*] indicate significance at the 10 (5) [1]% level. The DOLS results are based on a one lead/lag model

Table 11 Estimates of the long-run effect of R&D on IMR in developed countries

Independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RDGDP	-1.74* (-3.80)	0.92** (2.15)	-1.17* (-7.06)	-0.80** (-1.98)	-1.94** (-2.23)	7.89* (15.39)	-2.00** (-2.27)	-1.63* (-6.67)
RDGDPDRDP		-0.005* (-8.70)				-0.01* (-12.84)		
RDGDPPR			-0.006*** (-1.85)				-0.02* (-3.15)	
RDGDPPNR				-0.02* (-4.14)				-0.26* (-3.26)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DOLS	No	No	No	No	Yes	Yes	Yes	Yes
FMOLS	Yes	Yes	Yes	Yes	No	No	No	No
Sample period	2001–2017	2001–2017	2001–2017	2001–2017	2002–2016	2002–2016	2002–2016	2002–2016
Countries	15	15	15	15	15	15	15	15
Observations	239	239	239	239	215	215	215	215

The dependent variable is LE, and *t*-statistics are in parenthesis

*** (**) [*] indicate significance at the 10 (5) [1] % level. The DOLS results are based on a one lead/lag model

to find the long-run association between health status and R&D activities in developing countries, we introduce an autoregressive distributed lag model (ARDL). Moreover, we use two different estimators such as follows: the mean group (MG), the pooled mean group (PMG) estimators in order to reveal both the long-run and short-run effects of innovation in terms of R&D activities on population health of developing world.

Tables 12 and 13 report the results based on the PMG estimators and MG estimators. The equations for the long-run association between LE (or IMR) and RDGDP were calculated for the panel of developing countries. From these results, the MG was estimated from the unrestricted country by country estimation. Coefficients of MG estimator are the average of country-specific parameters, and PMG coefficients are restricted to be the same across countries. Therefore, the coefficients of PMG estimators (long-run slope homogeneity) and coefficients of MG estimators (long-run slope heterogeneity) illustrate how the empirical estimations of the population health of developing nations are sensitive to R&D activities under different estimations techniques.

According to the Hausman test (see row 5 of Tables 12 and 13), we accept the coefficient of PMG estimators as efficient and consistent estimator. In line with the developed countries' estimation, the PMG estimator outcomes indicate the existence of a strong relationship between health status and innovation in labor-rich countries, in the short and long-run. As one would not expect, we can notice that the long-run marginal effect of innovation either in terms of RDGDP or in terms of different interaction terms on population health is of the same sign as in short-run impact. Similar to that of the earlier panel, here, we also get three threshold values of the additional three R&D-related indicators as RDP*, PR*, and PNR* for which a positive impact of RDGDP on population health of developing countries can be found. From Tables 12 and 13, we find the threshold values and they are as follows: RDP* can take a value within the range of 114 to 218, PR* varies within the range of 45 to 125, and PNR* should take the value in between 4 and 5.

Health Forecast and Innovation

Only one hidden layer has been used while the number of neurons in the hidden layer has been varied at four levels (10, 20, 30, and 40 numbers of neurons). A delay of 2 units to consider the lagged values of both dependent and independent variables has been considered for model building. The number of neurons in the hidden layer is varied at four levels, and five learning algorithms have been used. Five back-propagation algorithms, namely, Levenberg–Marquardt (LM), scaled conjugate gradient (SCG), conjugate gradient with Powell–Beale restarts (CGB), Fletcher–Powell conjugate gradient (CGF), and Polak–Ribière conjugate gradient (CGP) are used for training.

Figures A.F.1, A.F.2, A.F.3, A.F.4, A.F.5 and A.F.6 (Figures A.F.7 and A.F.8) graphically represent association of the actual and predicted LE (or IMR) for all training, test, and validation sample. The magnitude of error in terms of MAE, MAPE, and MSE are illustrated in Figures A.F.5 and A.5.7. Although graphical representation strongly suggests goodness of fit of NARX network in LE (or IMR) in presence of RDGDP, for quantitative justification, Table 14 is drawn for training and test dataset.

Table 12 Estimates of the long-run effect of R&D on LE in developing countries

Independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Long-run coefficients								
RDGDP	0.66* (0.00)	2.27* (0.00)	3.11** (0.03)	1.02* (0.00)	0.45 (0.35)	2.02* (0.00)	0.51** (0.03)	1.02* (0.00)
RDGDPRDP		-0.02** (0.04)				1.25 (0.24)		
RDGDPPR			-0.07*** (0.08)				-0.36*** (0.06)	
RDGDPPNR				-0.21* (0.01)				-0.51** (0.03)
Hausman Test	14.37 (0.00)							
Error correction coefficient	-0.31* (0.00)	-0.20** (0.05)	-0.05** (0.03)	-0.50** (0.03)	-0.20** (0.05)	1.13** (0.05)	-0.15* (0.00)	-0.35** (0.04)
Short-run coefficients								
Δ RDGDP	0.04** (0.05)	-2.15 (0.12)	-0.04** (0.05)	4.43* (0.01)	0.55* (0.03)	0.15 (0.12)	-0.21 (0.15)	1.43 (0.21)
Δ RDGDP(-1)				1.04 (0.71)				0.04** (0.07)
Δ LE(-1)	-0.14*** (0.08)		-0.54* (0.01)	-0.39*** (0.09)	0.14 (0.24)	-0.02* (0.01)	-1.54** (0.04)	-0.09** (0.04)
Δ RDGDPRDP		-0.93 (0.74)				-0.43 (0.14)		
Δ RDGDPPR			-0.35** (0.07)				-0.13** (0.07)	
Δ RDGDPPNR				-1.47* (0.00)				-2.31* (0.00)
Linear Trend	0.01 (0.73)	0.01 (0.35)	-0.04 (0.13)	0.01* (0.01)	0.90 (0.33)	0.05 (0.53)	-0.14** (0.03)	0.21 (0.31)

Table 12 (continued)

Independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	9.09 (0.13)	7.49 (0.15)	0.34* (0.00)	36.69** (0.02)	1.25** (0.03)	3.41** (0.05)	7.17* (0.00)	36.69 (0.12)
PMG	Yes	Yes	Yes	Yes	No	No	No	Yes
MG	No	No	No	No	Yes	Yes	Yes	No
Lag structure	ARDL(2,1)	ARDL(1,1,1)	ARDL(2,1,1)	ARDL(2,2,1)	ARDL(2,1)	ARDL(2,1,1)	ARDL(2,1,1)	ARDL(2,2,1)
Sample period	2001–2017	2001–2017	2001–2017	2001–2017	2004–2017	2004–2017	2004–2017	2004–2017
Countries	17	17	17	17	17	17	17	17
Observations	239	239	239	239	215	214	215	215

The dependent variable is LE and *P*-values are in parenthesis.

*** (**) [*] indicate significance at the 10 (5) [1] % level. Under the long-run slope homogeneity, the Hausman statistic is asymptotically distributed as a chi-squared with corresponding degrees of freedom.

Table 13 Estimates of the long-run effect of R&D on IMR in developing countries

Independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Long-run coefficients								
RDGDP	-1.23* (0.00)	-2.18* (0.00)	-3.73** (0.03)	-2.23* (0.00)	-1.45** (0.05)	-1.02* (0.00)	-1.51 (0.23)	-1.31** (0.04)
RDGDPRDP		0.01** (0.03)				3.41 (0.77)		
RDGDPPR			0.03* (0.00)				1.36*** (0.09)	
RDGDPPNR				0.71* (0.00)				-1.21** (0.04)
Hausman Test	14.51–15.15 (0.00) (0.00)							
Error correction coefficient	-0.01* (0.00)	-0.30** (0.05)	-0.35** (0.03)	-0.05** (0.03)	-1.30** (0.05)	1.13 (0.25)	-0.29** (0.02)	-1.41** (0.04)
Short-run coefficients								
Δ RDGDP	-1.24** (0.05)	-2.75** (0.02)	-0.34** (0.05)	-1.43* (0.00)	-1.15** (0.03)	0.42** (0.02)	-0.21** (0.05)	-1.43** (0.01)
Δ RDGDP(-1)	0.15** (0.02)			1.04** (0.02)				0.34** (0.07)
Δ IMR(-1)	-0.17* (0.00)		-0.14* (0.00)	-0.39* (0.00)	3.14 (0.44)	-0.12* (0.00)	-0.04* (0.00)	-0.03** (0.02)
Δ RDGDPRDP		-0.93 (0.74)				-0.03 (0.34)		
Δ RDGDPPR			0.35* (0.00)				1.13** (0.07)	
Δ RDGDPPNR				0.02*** (0.09)				2.01* (0.00)
Linear Trend	0.21 (0.73)	0.01 (0.35)	0.14* (0.00)	0.11* (0.00)	0.90 (0.33)	0.15 (0.53)	0.14** (0.03)	1.01 (0.51)

Table 13 (continued)

Independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	10.12 (0.23)	17.45 (0.75)	11.34* (0.00)	36.69** (0.02)	75.25 (0.53)	5.10 (0.65)	21.17* (0.00)	26.39 (0.22)
PMG	Yes	Yes	Yes	Yes	No	No	No	Yes
MG	No	No	No	No	Yes	Yes	Yes	No
Lag structure	ARDL(2,2)	ARDL(1,1,1)	ARDL(2,1,1)	ARDL(2,2,1)	ARDL(2,1)	ARDL(2,1,1)	ARDL(2,1,1)	ARDL(2,2,1)
Sample period	2001–2017	2001–2017	2001–2017	2001–2017	2004–2017	2004–2017	2004–2017	2004–2017
Countries	17	17	17	17	17	17	17	17
Observations	239	239	239	239	215	214	215	215

The dependent variable is LE and *P*-values are in parenthesis.

*** (**) [*] indicate significance at the 10 (5) [1]% level. Under the long-run slope homogeneity, the Hausman statistic is asymptotically distributed as a chi-squared with corresponding degrees of freedom.

Table 14 Performance on training dataset of LE and IMR for both panels

Variable	DOLS			NARX		
	Panel: <i>Developed countries</i>					
	MAE	MAPE	MSE	MAE	MAPE	MSE
LE	0.8350	1.0369	1.0848	0.0325	0.7351	0.0125
IMR	0.3441	2.2230	0.4434	0.1224	0.8934	0.0798
	ARDL			NARX		
	Panel: <i>Developing countries</i>					
	MAE	MAPE	MSE	MAE	MAPE	MSE
LE	0.2418	0.3000	0.3224	0.1249	0.2416	0.1237
IMR	0.0164	0.4822	0.0229	0.0151	0.0201	0.0196

Source: author's calculation.

Statistics of MAE, MAPE, and MSE of predictive modeling performance of NARX network on training and test dataset of LE (or IMR) owing to RDGDP for all experimental trials are summarized in Table 14.

Table 14 reveals that neural network-based NARX technique outperforms both DOLS and ARDL for their respective panel. It is to be noted that NARX network with 2 delay units has predicted LE (or IMR) as a nonlinear function of innovation or R&D activities in terms of RDGDP.

Concluding Remarks and Policy Implications

In this paper, we have considered health-related and research and development (R&D)–related data of fifteen developed and fifteen developing countries for the time period 2000–2017. The dependent variables of our work are IMR and LE which represent the health status of a nation. The independent variables which we have considered are percentage of GDP spend for R&D, the number of persons involved in research and development, patent rights of residents, and nonresidents. We have tried to estimate the short-run and long-run effects of R&D-oriented variables on health status of a nation by the help of panel regression. For that purpose, all the necessary tests have been performed. For long-run estimation, we have used both DOLS and FMOLS techniques for developed nations, since panel data for developed nations follow same orders. For developing nations, in case of long-run estimation, we have applied ARDL model to deal with the stationary series problem of different orders. For the developed nations, we have found bilateral causality between RDGDP and LE as well as IMR in the short run, found by the Wald test. The Pedroni test depicts the existence of long-run equilibrium relations between R&D and LE, and R&D and IMR. For developed economies, in the long run, we have seen significant impacts of R&D-related variables on the health status. For the developing nations, we have used MG and PMG estimators to see the effects of innovations in R&D on health of a nation, for both short run and long run. For developing countries also, we can see strong association between R&D-related variables and health status. In other words, our conclusions support that these countries need R&D activities in health with high frequency instead of the traditional type of investment in health to promote population health to the next trajectory.

Next, we have applied neural network methods for the purpose of accurate prediction from our panel analysis. Here, we have seen the long-run prediction by NARX model has been the best one, for both developed and developing countries, when compared with the outcomes of both DOLS and FMOLS. NARX model has also strong connection between R&D-related variables and health status.

Moreover, we find that the increased number of patent registration by foreigners for developed countries and increased number of patent registered by foreign and domestic nationals increased numbers person presence in R&D and positive growth of R&D expenditure as a percentage of GDP may stimulate economic growth and development. Thus, as policy implications, it seems important that these countries must promote their attractiveness of investments in health in the form of high-quality R&D activities which can bridge technological and resource gap among nations.

Appendix

Fig. A.F.1 Impulse Responses between LE and RDGDP

Fig. A.F.2 Variance decomposition between LE and RDGDP

Fig. A.F.3 Impulse Responses between IMR and RDGP

Fig. A.F.4 Variance Decomposition between IMR and RDGP

Note-

Fig. A.F.5 Best Validation Performance of LE

Fig. A.F.6 Performance of NARX in case of LE

Fig. A.F.7 Best Validation Performance of IMR

Fig. A.F.8 Performance of NARX in case of LE

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