

The Relationship Between Life Expectancy And Technological Development: Evidence From India

Jasneet Kaur Wadhwa¹, Srividya Subramaniam²

¹(Associate Professor, Department of Economics, SGTB Khalsa College, India)

²(Associate Professor, Department of Economics, SGTB Khalsa College, India)

ABSTRACT:

This paper examines the relationship between life expectancy and technological development in India. Using patents as a proxy for technological development econometric tests are conducted using annual data for the period 1984-2019. Both the series are found to be non-stationary and integrated of order (1), following the logarithmic transformation based on the Augmented Dicky Fuller test. The findings of the Johansen cointegration test support the absence of a long-run equilibrium relationship between the two variables. Granger causality tests indicate the absence of causality between life expectancy growth and growth in patents. These results are in contrast to a similar study conducted in the USA by Singh et al. (2020), which found a positive correlation between technological development and life expectancy. The absence of a significant relationship highlights the need for further investigation into other potential factors that may affect life expectancy in India, such as literacy rates, education, and healthcare expenditure.

KEY WORDS: Patents; Life Expectancy; Cointegration; Causality

Date of Submission: 03-09-2023

Date of Acceptance: 13-09-2023

I. INTRODUCTION

Researchers have shown increased interest in technological development, as it is considered to be an important driver of economic growth and the measurement of technological change is becoming increasingly important in business, research and policy. However, measuring technological development is a difficult task. Technological development/Innovations can either be product innovation and/or process innovation. Process innovation involves the know-how contained in patents, licences, design and Research and Development activities. With some exceptions, the most innovative industries in terms of business process innovation are among those reporting the highest product innovation rates, indicating considerable synergies between different types of innovations (source-oecd.org). Thus, indicators like patents, scientific and technical research publications/articles and expenditure on research and development have been used as a proxy by various researchers to measure the extent of technological development.

‘A patent is a type of intellectual property that gives its owner the legal right to exclude others from making, using, or selling an invention for a limited period in exchange for publishing an enabling disclosure of the invention.’ (source-wikipedia.org). The World Intellectual Property Organization (WIPO) serves as a global forum for intellectual property (IP) services, policy and information. It is a self-funding agency of the United Nations, with 193 member states, established in 1967. According to WIPO, one of the rationales for patents is that they stimulate economic and technological development and promote competition by creating a financial motivation for invention in return for the disclosure of the invention to the public.

Scientific publications are another important source of codified knowledge measuring technological development. They represent the knowledge generated in the public sector, particularly in universities and other publicly funded research centres. We are compelled to rely on the sources that are accessible since there is a shortage of information on all the scientific literature that has been published worldwide. Among them, the most comprehensive and validated is the Science Citation Index generated by the Institute for Scientific Information. It reports information on the technical and scientific articles published in a sample of over 8,000 international journals, with a focus primarily on science, even though a significant and growing share of articles is published by researchers working in the business sector. The journals included are also biased towards the English language (source-oecd.org).

Expenditure on research and development is yet another indicator of technical development. Resources devoted to research and development are probably a better indicator than the combination of patents and scientific

papers, but data for the majority of developing countries are not reliable or available. R&D data for developing countries are too often overestimated.

Many studies have used patent data as a proxy for technological development. Archibugi and Pianta (1996) have reviewed the developments in the measurement of technological change using patent data and indicators derived from innovation surveys. To describe a country's relative technological position and its relative specialisations, several studies have analysed industrial patterns of innovation across nations. For this purpose, patent data have been widely used to examine the strengths and weaknesses in the technological fields. Soete and Wyatt (1983) have compared and analysed the foreign patenting activity in some of the world's major patent systems and suggest that foreign patent data might provide a very useful addition to the arsenal of Science and Technology Output Indicators.

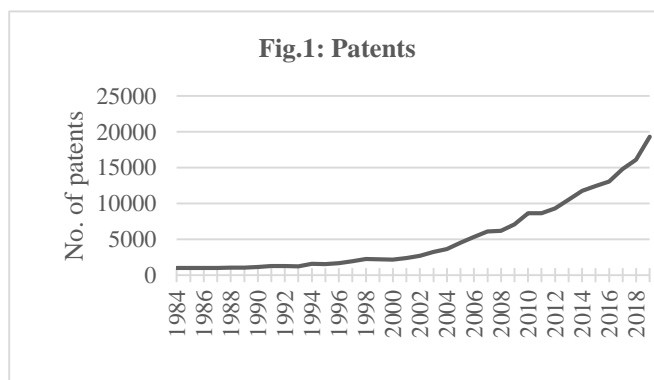
To investigate the impact technology has on the performance of countries and industries, several studies have related patent data to economic indicators, either at the national level or when investigating industrial patterns. Patent data have been used to explore the relationship between technology and trade. Aghion et al. (2018) have investigated the effect of export shocks on innovation. They have used a patent dataset from the European Patent Office as a proxy for innovation. In a very recent study, Nguyen et al. (2022) examined the impact of inventions, measured by the number of new patents, on economic growth for 43 countries in the period 1998 to 2016.

Not all inventions are technically patentable and not all inventions are patented. Despite this limitation, patents are considered a good proxy for technological inventions. Patents are a direct outcome of innovative processes and show the direction of technological progress. The availability and ease of access to patent-related information and the regular updating of databases by Intellectual Property Offices allow for very close monitoring of technological innovation. Another advantage of using patent data is that the data source is validated by an external source. Thus, we have used the data on patents as a proxy for technological development for our study.

Evolution of Patents in India

Patent law's primary goal is to promote scientific studies, economic development, and innovative technology. The Indian Patents & Designs Act, of 1911, was revised in 1920, 1930 and again in 1950 after independence. The patent legislation was established in 1970 and was put into effect on April 20, 1972, with the release of the Patent Rules, 1972. The Patents (Modification) Act of 2002 was the second amendment to the 1970 Act (Act 38 Of 2002). With the adoption of the new Patent Rules, 2003, which superseded the earlier Patents Rules, 1972, this Act became effective on May 20, 2003. The Patent Rules of 2003 were revised in 2005 and again in 2006. The inclusion of shorter timelines and a price system based on specified size and many claimants, and a minimum fee are key aspects of both the 2005 and 2006 Rule (source <https://vakilsearch.com/blog/the-brief-history-of-patent-system-in-india>).

Figure 1 on patents shows the exponential growth in the number of patents filed in India for the period of study. The number rose from 1003 in 1984 to 1048 in 1989, showing an average annual increase of about one per cent per annum for the period. The annual growth rate of patents was much higher (9-10%) in 1990-1991, This could be due to the economic reforms and opening up of the economy. The annual growth rate went up to 31% in 1994. Despite the amendment of the Act in 1995, the numbers started falling, increased for a couple of years and then the annual growth rate dipped to negative one per cent in 2000.



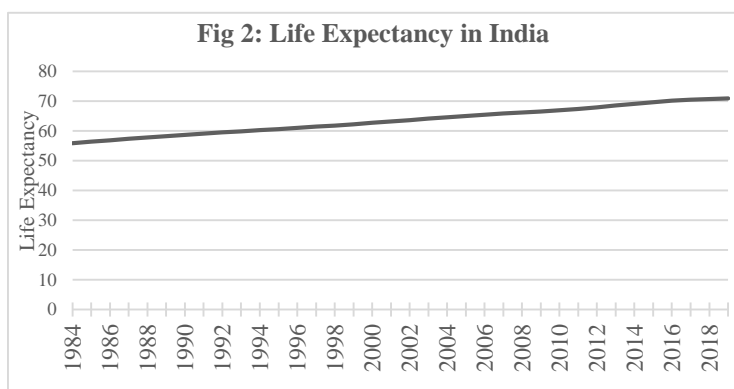
*Source: <https://www.wipo.int>

In the Patents (Amendment) Act 2002, new rules were adopted. In 2003, the number of patents filed showed an annual growth rate of 19.5%. Again, the act was modified in 2005 and 2006. The inclusion of shorter timelines and a price system based on specified size and many claimants and a minimum fee were the key aspects

of both the 2005 and 2006 Rules. The annual growth rate was 25% in 2005 and 17% in 2006. In 2008, again the growth slowed down owing to the global recession. The number of patent filings increased from 8625 in 2011 to 19306 in 2019 due to steps taken by the government to strengthen the intellectual property rights (IPR) regime of the country, which has led to increased awareness among all strata of society. Overall, the number of patents has increased from 1003 in 1984 to 19,306 in the financial year 2019, showing an average annual growth rate of 11-12% in the last two decades.

Life Expectancy in India

Life expectancy is a statistical measure of the average number of years that a newborn could expect to live if he or she were to pass through life exposed to the sex- and age-specific death rates prevailing at the time of his or her birth, for a specific year, in a given country, territory, or geographic area. It is calculated by dividing the number of deaths in a given population over a particular period by the total population. Life expectancy is an important measure of population health and is used to assess the effectiveness of public health interventions and healthcare systems.



*Source: <https://www.who.int>

Figure 2 on life expectancy shows that in the last 35 years, there is an increase of approximately 15 years of life span for every Indian. In 1984 the life expectancy of Indians was only 55.8 years. It increased to 70.91 in 2019. There are various reasons for this slow growth like toxic air, nutrition, public health services, hygienic conditions and climate changes. As per the World's State of Global air-2020 report, India is on top rank as far as air pollution is concerned. The average annual growth rate in the eighties was 0.85%. In the nineties, it was 0.66%, then 0.67% in 2000-2009 and finally 0.64% in 2010-2019. Compared to the developed country like the USA, the life expectancy in India is quite low. This can be attributed to the higher burden of non-communicable diseases, such as diabetes and heart disease, air and water pollution, poor sanitation and malnutrition, lack of access to healthcare, high infant mortality rates etc (sources-www.nytimes.com; www.thelancet.com).

The objective of this paper is to determine if there is a long-term relationship between life expectancy and technological development proxied by patents for the case of India for the period 1984-2019. With reference to this relationship, we aim to study the effect of life expectancy on technological development.

The paper is structured as follows. The next section discusses the review of the literature. Data and the econometric methodology followed are given in Section 3. Section 4 contains the empirical results, followed by the conclusions in Section 5.

II. REVIEW OF LITERATURE

Technological development improves life expectancy. Many studies show that technological advancements enhance the average life expectancy. Miah and Omar (2012) have shown that in countries with lower technological usage, life expectancy is about fifty percent of that of the advanced nations. Similarly, Banerjee et al. (2014) have demonstrated that technology innovation has played a significant role in India's recent economic growth. On the other hand, there is a possibility that the causality runs in the opposite direction i.e. Longer life expectancy leads to increased technological development.

According to Galor and Stark (1992), increased life expectancy leads to economic growth. Cervellati and Sunde (2005) and Acemoglu and Johnson (2007) reached similar conclusions using different models. Turan (2009) has shown that an increase in life expectancy has a positive impact on growth even in less developed countries. Growth, in turn, provides conditions favourable to technological progress, such as urbanisation, employment opportunities, and research investment availability. More recently, in their paper, Singh et al. have also challenged the conventional economic models that suggest that technological advancement leads to an

increase in life expectancy. Their paper, based on modelling on data from the USA over the last 150-200 years, concludes that life expectancy is in fact the cause and technological development is the effect. This paper attempts to empirically test the validity of life expectancy as an important factor contributing to technological development in India, inspired by the results of Singh et al (2020).

This paper makes an important contribution to the existing literature by testing the role played by life expectancy as an important explanatory variable in determining technological progress in a developing country like India. The objective of this paper is to determine if there is a long-term relationship between life expectancy and technological development proxied by patents for the case of India for the period 1984-2019.

III. DATA AND ECONOMETRIC METHODOLOGY

Data

The study uses annual data on India for the period 1984-2019. For patents data on direct applications (residents) from the office of origin have been used. This data has been obtained from the WIPO statistics database. The measure for the life expectancy variable is life expectancy (in years) taken from World Development Indicators. The variable patent has been represented by P and life expectancy by L in this paper.

Econometric Methodology

In this paper, we are studying time series data. Hence it becomes pertinent to first know about the stationarity of the variables. This is because if we regress a non-stationary series on one or more non-stationary series it will give rise to spurious or nonsense regression. However, if the time series are stationary then the regression may not be spurious. In addition, even though the two series individually may be non-stationary but if they are found to be cointegrated, then regression using these two series may not be spurious (Gujarati and Porter (2010)). After testing for stationarity, if the variables are non-stationary in levels, then their order of integration is checked. According to Engle and Granger (1987) if two series X and Y which are each integrated of order 1 are found to be cointegrated then there would be the existence of causal relation in at least one direction.

In this paper, we follow the methodology given by Oxley and Greasley(1998). This is a three-stage procedure which tests the direction of causality. First, the order of integration of the natural log of the series is found out by employing the Augmented dicky Fuller test. The optimal lag length is chosen using the SIC criterion so that the error term is stationary. If the null hypothesis of non-stationary is not rejected then the series is non-stationary. In the following stage, the bivariate cointegration is employed using the VAR approach of Johansen (1988, 1999) and Johansen and Juselius (1990). Once both series are found to be I(1) in step 1, the next step is to test for cointegration. In the third stage, standard Granger-type causality tests are conducted. If bivariate cointegration is not established (which is the case in this study) then this becomes the second stage. If the series are found to be (1) but not cointegrated then they have to be transformed to make them I(0) before applying Granger-type tests.

So, the equation

$$\Delta X_t = \alpha + \sum_{i=1}^m \beta_i \Delta X_{t-i} + \sum_{j=1}^n \gamma_j \Delta Y_{t-j} + u_t$$

$$\Delta Y_t = a + \sum_{i=1}^q b_i \Delta Y_{t-i} + \sum_{j=1}^r c_j \Delta X_{t-j} + u_t$$

Optimum lag length m, n, q and r are determined based on AIC and or SBC.

$$\text{For } H_0: \gamma_1 = \gamma_2 = \dots = \gamma_n = 0$$

$$H_A: \text{at least one } \gamma_j \neq 0, j = 1, 2, \dots, n$$

then ΔY_t will Granger cause ΔX_t if H_0 is rejected.

On the other hand, ΔX_t will Granger cause $\dots \Delta Y_t$ if

$$H_0: c_1 = c_2 = \dots = c_n = 0 \text{ is rejected against } H_A: \text{at least one } c_j \neq 0$$

IV. EMPIRICAL RESULTS AND INTERPRETATION

The series of P and L are displayed in Fig.1 and 2 respectively. A cursory analysis of this graph plotting the two variables of the study shows that they are non-stationary. Logarithmic transformation of the two variables is done before starting the estimation process. LL and LP are the series of L and P after logarithmic transformation. The descriptive statistics for both series are given in Appendix, table 1.

In the first step in our methodology, in order to know the order of integration, we test the presence of unit roots of both the series. The stationarity test was conducted using the Augmented Dicky Fuller test with intercept and intercept plus trend. Results of the Augmented Dicky Fuller test on the levels of LP and LL are given in Table No. 1. Based on the calculated ADF test statistic, its p-value and critical values we find that the null hypothesis of non-stationarity in both series cannot be rejected. This means both series contain a unit root. Next is the ADF test on the first differences of LL and LP results which are also given in Table 1. When the ADF test is conducted on the first difference of both the series we find that the null hypothesis of non-stationarity is rejected for both variables which implies that the differenced series is stationary (Table No.1). Hence LP and LL are I (1).

Table No. 1. Results of Augmented Dicky Fuller tests

Variable	Constant, No trend		Constant, Trend	
Levels	ADF Test statistic	p-value	ADF Test-statistic	p-value
LP	1.738(-3.632,-2.948,-2.613)	0.995	-2.779(-4.234,-3.544,-3.205)	0.2143
LL	-3.121(-3.639,-2.951,-2.614)	0.0353	-3.126(-4.267,-3.553,-3.209)	0.117
First Difference				
LP	-5.381(-3.639,-2.951,-2.614)	0.0001	-5.89(-3.548,-3.207)	0.0001
LL	-4.052(-3.661,-2.960,-2.619)	0.0038	-4.223(-4.296,-3.568,-3.218)	0.0118

Note: Values in parenthesis are critical values for ADF statistic at 99%, 95%, and 90% respectively.

Once we obtain both series as I(1) we check for cointegration using Johansen methodology. Results of the Johansen methodology are given in Table 2. The cointegration rank of the two series is tested using the maximum eigen value statistic and trace statistic. Beginning with the null hypothesis of $r = 0$ i.e. no cointegration among the variables, the maximal eigenvalue statistic is 9.072 which is less than the 95% critical value of 15.495. Thus, the null hypothesis of no cointegration is not rejected at 5% level of significance. Next, the trace test gives a statistic of 8.078 which is less than the 95% critical value of 14.264. on this basis, the null hypothesis of no cointegration is not rejected. Thus, the results of both the trace and maximum eigen value statistics indicate the absence of cointegration between the two variables LL and LP. This means we cannot predict one variable using past values of the other variable.

Table No. 2. Results of Johansen-Juselius Cointegration tests

Null	Alternative	Statistic	95% critical value	p-value
Max. eigen value test				
$r = 0$	$r = 1$	9.072	15.495	0.358
$r \leq 1$	$r = 2$	0.994	3.841	0.318
Trace test				
$r = 0$	$r \geq 1$	8.078	14.264	0.370
$r \leq 1$	$r = 2$	0.994	3.841	0.318

Note: r is the number of cointegrating relations

In the absence of cointegration, we use standard Granger causality tests to study the direction of causality between the variables LP and LL. Since both series are individually I(1) we have used the first difference of the series and computed the Granger causality tests. Therefore, we model the bivariate system DLL and DLP where D refers to the first difference (and hence defines the growth of the corresponding variable). The results of the Granger Causality tests are given in Table 3. These results show that there is no causal relationship between DLL and DLP. This means that it is unlikely that growth in life expectancy causally led to growth in patents which is a proxy for technological development.

Table No. 3. Granger causality results

Null Hypothesis	Chi-sq. statistic	p-value
DLP does not Granger cause DLL	1.535	0.464
DLL does not Granger cause DLP	2.150	0.341

V. CONCLUSIONS

In this paper, we have examined the relationship between technological development and life expectancy in India for the period of 1984-2019 using annual data. The measure for technological development was based on the number of patents filed during the study period. Our empirical results suggest that there is no cointegration between these two variables, indicating that there is an absence of any long-term relationship between technological development and life expectancy in the Indian case.

Interestingly, these findings stand in stark contrast to those obtained by Singh et. al. (2020) in their study of a developed country viz. the USA. A possible explanation for the contrasting results could be attributed to several factors. Firstly, the period of study in India was only 36 years, compared to a much longer 150 years in Singh et.al.'s study, which may have had a significant impact. Secondly, it is essential to note that research and development expenditures in India are significantly lower than those in the USA, which might play a significant role in this disparity. This is a vital consideration since it is well-established that investment in R&D has a direct impact on research outcomes and can significantly influence results. As such, it is plausible that this factor played a crucial role in the divergent findings observed.

Furthermore, our analysis shows that throughout the study period, the number of patents filed in India has been considerably lower than in the USA. The absence of a significant relationship between these two variables in India may be pointing towards/indicative of other crucial variables that have not been factored in such as literacy rates, secondary and higher education, and health expenditures. Thus, it is crucial that further testing be done with

these variables to determine their significance and their impact on the economic development of a country. The contrast in results between our findings and those of Singh et al. (2020) highlights the importance of studying countries at various stages of development and durations when examining relationships between vital aspects like technology and life expectancy. It is also possible that the discrepancy with regard to literacy, education and expenditure for research and development between India and the US may play a role in explaining the difference in our findings.

Appendix

Descriptive statistics

	LL	LP
Mean	4.148016	8.108894
Median	4.148722	7.834739
Maximum	4.261411	9.868171
Minimum	4.022061	6.889591
Std. Dev.	0.072050	0.986050
Skewness	-0.040040	0.274710
Kurtosis	1.832363	1.628071
Jarque-Bera	2.054683	3.276079
Probability	0.357957	0.194361
Sum	149.3286	291.9202
Sum Sq. Dev.	0.181694	34.03028
Observations	36	36

REFERENCES

- [1]. Aghion P., Bergeaud A., Lequien M. And Melitz M. (2018). The Impact Of Exports On Innovation: Theory And Evidence. NBER Working Paper No. 24600. © 2018 B.
- [2]. B. Turan. (2009). Life Expectancy And Economic Development: Evidence From Microdata. Working Paper.
- [3]. D. Acemoglu, S. Johnson. (2007). Disease And Development: The Effect Of Life Expectancy On Economic Growth. Journal Of Political Economy ISSN 0022-3808, 115, 925 (2007).
- [4]. D. Archibugi And M. Pianta. (1996). Measuring Technological Change Through Patents And Innovation Surveys. Technovation, 16(9) (1996) 451-468 Copyright © 1996 Elsevier Science Ltd Printed In Great Britain.
- [5]. Engle, R. F., & Granger, C. W. (1987). Co-Integration And Error Correction: Representation, Estimation, And Testing. Econometrica: Journal Of The Econometric Society, 251-276.
- [6]. Gujarati, D. N., & Porter, D. C. (2010). Essentials Of Econometrics (Vol. 4th, International). Boston, MA.
- [7]. Johansen, S. (1988). Statistical Analysis Of Cointegration Vectors. Journal Of Economic Dynamics And Control, 12(2-3), 231-254.
- [8]. Johansen, S. (1991). Estimation And Hypothesis Testing Of Cointegration Vectors In Gaussian Vector Autoregressive Models. Econometrica: Journal Of The Econometric Society, 1551-1580.
- [9]. Johansen, S., & Juselius, K. (1990). Maximum Likelihood Estimation And Inference On Cointegration--With Applications To The Demand For Money. Oxford Bulletin Of Economics And Statistics, 52(2), 169-210.
- [10]. M. Cervellati, U. Sunde. (2005). Human Capital Formation, Life Expectancy And The Process Of Development. The American Economic Review ISSN 0002-8282, 95, 1653.
- [11]. M. Miah, A. Omar. (2012). Technology Advancement In Developing Countries In Digital Age. International Journal Of Science And Applied Information Technology, ISSN 2278 – 3083, 1, 30.
- [12]. Nguyen, Canh Phuc & Doytch, Nadia, (2022). The Impact Of ICT Patents On Economic Growth: International Evidence. Telecommunications Policy, Elsevier, Vol. 46(5).
- [13]. O. Galor, O. Stark (1992). Life Expectancy, Human Capital Formation And Per Capita Income. Vienna Economics Papers Vie9305, University Of Vienna, Department Of Economics.
- [14]. Oxley, L., & Greasley, D. (1998). Vector Autoregression, Cointegration And Causality: Testing For Causes Of The British Industrial Revolution. Applied Economics, 30(10), 1387-1397.
- [15]. Phillips, P. C., & Perron, P. (1988). Testing For A Unit Root In Time Series Regression. Biometrika, 75(2), 335-346. R.
- [16]. Banerjee And S. S. Roy. (2014) Human Capital, Technological Progress And Trade: What Explains India's Long-Run Growth? Journal Of Asian Economics, ISSN 1049-0078, 30, 15.
- [17]. Singh, A., Kumar, K., Wadhwa, J. K., & Arun, P. (2020). Effect Of Life Expectancy On Technological Development. Technium Soc. Sci. J., 5, 225.
- [18]. Soete, L.G., Wyatt, S.M.E. (1983). The Use Of Foreign Patenting As An Internationally Comparable Science And Technology Output Indicator. Scientometrics 5, 31-54.