Estimating the Impact of Human Capital Underutilization on the Productivity and Economic Growth in India

Vijaya Kumar M. · Balu B.

Received: 20 October 2021 / Accepted: 21 February 2023
© The Author(s), under exclusive licence to Springer Science+Business Media, LLC, part of Springer Nature 2023

Abstract
The study investigates the impact of human capital underutilization on India’s economic growth and labor productivity. For this purpose, we have employed the Autoregressive Distributed Lag (ARDL) model, which was applied using the annual time series data from 2005 to 2019. The ARDL estimation results revealed that human capital underutilization has a negative but statistically insignificant relationship with economic growth in the long run. We also found that a short-run decrease in time-related underemployment increased labor productivity. Therefore, we recommend that the policymakers consider human capital utilization measures from the perspective of both individuals and the economy, which should also be addressed in their policy framework. Furthermore, the empirical insights of the study could be helpful for future labor policy recommendations in India and emerging economies across the globe.

Keywords Human capital · Underutilization · Economic growth · Labor productivity · India

Introduction
India has witnessed an accelerated GDP growth trend during the last decades since the early 1980s, which further increased after the 1990s due to the introduction of new economic reforms. Resilience is a remarkable feature of India’s growth story (Gupta & Blum, 2018). But paradoxically, the rapid growth has not transformed India’s labor market and employment conditions (Kundu & Mohanan, 2009). Anand et al. (2014) documented the evolution of inequality across Indian states during the
rapid growth period and found that a wide range of disparities was not appropriately addressed and suggested a strong urge for inclusive economic growth. Expanding the working-age share of the population can boost economic growth, as India is midway through its demographic dividend (Ministry of Finance, 2016). Similarly, social expenditures, especially on education, attainment of education rates, and skill development, have an essential role in fostering economic growth (Aggarwal et al., 2019; Grant, 2017; Mathai et al., 2020). India's economy is one of the fastest-growing economies in the world, and the service sector has led its growth, producing 47.69% of GDP, followed by 25.87% in industry and 16.77% in agriculture (Statista, 2022).

One of the essential components of the economic growth of a nation is its human capital, and a large body of literature confirms it has the potential to catalyze GDP and labor productivity (Helliwell, 2001; Lucas, 1988; Mankiw Gregory et al., 1992; Pelinescu, 2015; Wilson & Briscoe, 2004). According to endogenous growth theory, economic efficiency in human capital and improved skills and technologies have been considered the key source of economic growth (Viswanath et al., 2009). So allocating financial resources toward improving human capital could bring long-term sustained economic growth, as there is a strong positive correlation between human capital and economic growth in India (Shukla, 2017).

However, one of the pertinent issues faced by developing countries is the underutilization of human capital, which is detrimental to a nation’s economic growth and development (Union of International Associations, 1997). Human capital underutilization occurs when there is a mismatch between labor supply and demand (Hashem, 2021). But most of the previous empirical studies focused on unemployment as a measure of human capital underutilization and its impact on economic growth (Chand et al., 2018; Conteh, 2021; Khalid, 2021; Levine, 2013).

Even though the unemployment rate is considered a measure of labor underutilization, other types of underutilization exist, such as time-related underemployment, which includes situations where employees are willing to work for additional hours or have worked fewer than a selected number of hours (Greenwood, 1999). So eliminating unemployment is not enough to resolve human capital underutilization. As per the 3-year action agenda of Niti Aayog, 2017 India is facing a more severe problem of underemployment than unemployment (BusinessToday, 2017).

The contribution of our study to the existing literature lies in estimating the potential impact of human capital underutilization on economic growth and labor productivity. Moreover, the study provides policy recommendations for adequately utilizing India’s current and future labor forces.

We organized this paper into six sections. In addition to the introduction, the second section presents a brief literature review. The third section describes the study’s theoretical background. The fourth section outlines the data and methodology, while the fifth section presents the empirical results and analysis. Finally, the sixth section concludes the findings and provides policy recommendations.
Human capital formation is the outcome of investment in education, and the empirical evidence (Kukreja, 2013) revealed that education has a positive correlation with economic growth and development. According to Schundeln and Playforth (2014), in India, the contribution of education to economic growth has been a dynamic improvement in the country’s economic performance since 1980. Self and Grabowski (2004) proved that primary education in India has a strong and causal effect on economic growth. Barro (1991) also found that the productivity of human resources mainly depends on knowledge and skills possessed by the population, which enhance human capital and potentially promote economic growth.

Nauriyal et al. (2009) indicated that post-liberalization had increased the share of human capital in India over physical capital, significantly impacting the nation’s economic growth. Furthermore, Pelinescu (2015) investigated the relationship between human capital and economic growth and analyzed the presence of human capital in macroeconomic growth models. Viswanath et al. (2009) examined the human capital contributions to economic growth in India based on aggregate production function analysis. They employed cross-section data relating 1995–1996 and 1998–1999 of 26 Indian states and union territories. Their results show a strong positive correlation between investment in human capital and economic growth in India. Tsamadias and Prontzas (2012) empirically tested the interaction between the distribution of human capital, economic growth, and technological progress, and the results revealed that human capital has a positive impact on economic growth.

In fact, over the last few decades, many empirical studies have explored the positive relationship between human capital and economic growth (Barro, 2001; Cadil et al., 2014; Grant, 2017; Helliwell, 2001; Mankiw Gregory et al., 1992; Pelinescu, 2015; Shukla, 2017).

But one of the aspects that cause hindrance to human capital development is unemployment. Unemployment is a form of labor underutilization that causes human capital deterioration (Doppelt, 2019; Mimi et al., 2022; Samiullah, 2014). The unemployment rate is a key macroeconomic variable that indicates how well an economy uses its resources (Andrei et al., 2009).

A theoretical macroeconomic model (Doppelt, 2019) investigated and established the linkage of long-run economic growth and labor market dynamics and found that unemployment has negatively impacted economic growth and hindered further skill formation.

Okun’s law empirically illustrates the inverse relationship between a country’s unemployment and economic growth rates (Prachowny, 1993). Furthermore, several studies conducted worldwide have confirmed that unemployment has a negative relationship with economic growth (Al-Habees & Rumman, 2012; Andrei et al., 2009; Hjazeen et al., 2021; Kitov, 2021).

The empirical evidence of Chand et al. (2018) showed that GDP and unemployment have a strong negative correlation. Also, GDP accounts for 48% of the
change in the unemployment rate, whereas Padder and Mathavan (2021) analyzed the impact of economic growth on unemployment in India and found no strong linkage between these variables, and only 6% of the effect of economic growth on unemployment and the remaining 94% are by the influence of other factors, whereas the study by Bhowmik (2016) revealed that from 1991 to 2014, the relationship between GDP and unemployment growth rate in India was insignificant. Furthermore, Al-Habees and Rumman (2012), Chand et al. (2018), and Xia (2021) assessed the relationship between unemployment and economic growth in the context of India.

Sarbu and Cimpoies (2020) stated that labor underutilization is expressed by a need for an unsatisfied employment situation among the population in an economy where a difference between labor supply and demand exists. Underutilization of human resources has two forms: underutilization can arise due to unemployment; an individual cannot find any work but actively seek employment in a labor market. The second form of underutilization occurs in employment where a part-time individual wants to work full-time, or the current job does not fully utilize an individual’s skills (Glyde, 1975).

The unemployment rate is a measure of labor underutilization, but from the national economic perspective, unemployment and underemployment are regarded as underutilizing human resources, which is considered a gap between the actual output of goods and services produced and the expected that could have been realized (Sackey & Osei, 2006). Underutilizing human resources may result in high financial and social costs (Rodriguez Hernandez, 2018). Recently Hashem (2021) studied the impact of human capital underutilization in Egypt and found that it has a long-term negative impact on economic growth.

Most of the studies cited above have used the unemployment rate to quantify human capital underutilization and focused on estimating the relationship with economic growth while ignoring other measures of labor underutilization. The unemployment rate is a commonly used indicator of labor underutilization but provides only a partial picture of it (Hashem, 2021). In this study, we have used unemployment and time-related underemployment to analyze the impact of human capital underutilization on economic growth and labor productivity in India.

This study contributes multiple directions to the existing literature. Firstly, the study contributes to the existing literature of human capital underutilization by incorporating unemployment and time-related underemployment in the empirical analysis for India. Secondly, it analyzes the potential impact of human capital underutilization on economic growth and labor productivity. Thirdly, the study explores the problems of human capital and the trends of labor underutilization in India. Fourthly, this study suggests some key recommendations to policymakers that help for adequately utilizing the human capital of India.
Theoretical Background

Validity Okun’s Law

Okun’s law explains the relationship between aggregate output and an economy’s unemployment. According to Okun’s law, a shift in aggregate demand causes aggregate output to fluctuate around the potential. This leads organizations to hire new employees and the resulting employment rate shift in the opposite direction. A study conducted Bhat (2019) to assess the validity of Okun’s law in India revealed a negative relationship between economic growth and the unemployment rate in India. Their model suggests that a 1% increase in GDP will decrease the unemployment rate by 0.4%. Kim et al. (2020) and Hashmi et al. (2021) empirically validated Okun’s law in the context of India. Unemployment is considered a measure of labor underutilization and a significant decline in the rate of unemployment will have a direct and positive impact on the aggregate level of output and productivity.

\[ Et - Et^* = \gamma (Yt - Yt^*) + \eta t, \gamma > 0; \]  \hspace{1cm} (1)

\[ Ut - Ut^* = \delta (Et - Et^*) + \mu t, \delta < 0; \]  \hspace{1cm} (2)

where

\[ Et = \log \text{ of employment.} \]
\[ Yt = \log \text{ of output.} \]
\[ Ut = \text{unemployment rate.} \]
\[ * = \text{long-run level.} \]

Now the Okun’s Law can be derived by substituting (1) into (2):

\[ Ut - Ut^* = \beta (Yt - Yt^*) + \epsilon t, \beta < 0 \]  \hspace{1cm} (3)

where \( \beta = \gamma \delta \) and \( \epsilon t = \mu t + \delta \eta t \). The coefficient \( \beta \) in Okun’s law depends on the coefficients in the two relationships fundamental to the Law (Ball et al., 2013).

Human Capital in India

Human capital comprises of an individual’s educational, health, and other intangible competencies that can be used for an extended period. Human capital has the potential to increase countries’ productivity and economic growth. Human Capital Index (HCI) is the World Bank index that measures a country’s potential productivity. The overall value of HCI in India for 2020 is 0.49.

It indicates that a child born in India today will be only 49% as productive when he grows up as he could benefit from full health and complete education. The HCI value is higher than for the South Asia region and other lower-income countries (World Bank, 2020). Last year, India ranked 116th among the 157 countries in the world (Table 1).
Components of HCI

These are the major components or measurement matrix of the Human Capital Index (HCI).

- **Survival to Age**
  It indicates the probability of a child’s survival to age 5. World Bank (2020) reports that 96 children out of 100 born in India survive to age 5.

- **Expected Years of School**
  World Bank (2020) reports that a child in India expects to complete 11.1 of school by 18 years.

- **Harmonized Test Scores**
  It is the test score from international student achievement. As per World Bank (2020), the score for India is 399.

- **Learning Adjust Years of School**
  It refers to that what children learn and the expected years of schooling. For overall score for India is 7.01 (World Bank, 2020).

- **Adult Survival Rate**
  It is the rate of health risk; under the current conditions, a child born today has an adult survival rate of 83% in India (World Bank, 2020).

- **Not Stunted Rate**
  It is a healthy growth rate; for India, the value is 0.65 (World Bank, 2020). It indicates that 65 of 100 children in India have a healthy growth rate.

### Measurements of Human Capital and the Utilization of Adjusted Human Capital Index (UHCI)

The Human Capital Index (HCI) measures how the outcomes of current health and education conditions prevailing in a country influence the upcoming generations’ labor productivity. The Human Capital Index components are combined
into a single index by converting them into contributions to productivity (World Bank Group, 2020).

\[ \text{HCI} = \text{Survival} \times \text{School} \times \text{Health} \]

\[ \text{Survival} = \frac{1 - \text{under 5 mortality rate}}{1} \]

\[ \text{School} = e^{\Theta \left( \text{expected years of school} \times \frac{\text{Harmonized test score}}{625} - 14 \right)} \]

\[ \text{Health} = e^{\gamma_{\text{ASR}} (\text{Adult survival rate} - 1) + \gamma_{\text{stunting}} \times (\text{not stunted rate} - 1) / 2} \]

The resulting index has values that lie between 0 and 1. So a score of 0.75 indicates that a child born in today’s productivity is 25% lower than could be attained by complete education and health.

The Human Capital Index (HCI) indicates the quantum of human capital expected to accumulate by a child when he attains the age of 18, considering the country’s current education and health condition. It also helps to assess how changes in education and health influence workers’ productivity in the upcoming generation. A child born in a country is expected to grow up and become a future worker, assuming that he will find suitable work. It is said to be incorrect that a sizable proportion of the population in developing countries are unemployed/working in jobs that do not allow them to utilize their full skill and potential. The effective utilization of adjusted human capital will rectify the underutilization of human capital in labor markets (Pennings, 2020). The working-age population should effectively utilize their skills, abilities, education, and other potential to enhance productivity.

So the UHCI is supplementary measures of HCI are;

\[ \text{UHCI(basic or full)} = \text{Utilization rate(basic or full)} \times \text{HCI} \]

Basic UHCI = Income gains of potential [Unemployed] workers

Full UHCI = Increased employment rate + Gains from relocating workers to locations

\[ \text{Utilization (Basic measure)} = \frac{\text{Employment}}{\text{Working Age Population}} \]

\[ \text{Utilization(Full measure)} = \text{BER} \times 1 + (1 - \text{BER}) \times \frac{\text{Minimum HCI}}{\text{HCI}} \]

\[ \text{BER(Better Employment Rate)} = \frac{\text{Non} - \text{agriculture wage employees} + \text{Employers}}{\text{Population working age}} \]
The world bank analyzed the HCI utilization measures for more than 160 countries and discovered that GDP per capita would be $\frac{1}{\text{UHCI}}$ higher in a sphere of complete utilization of education can improve health (Akyuz, 2017).

### Problems of Human Capital in India

Human capital has a significant role in creating and developing aggregate economic growth in the country. Improving human capital will help to reduce poverty and foster the welfare of the people as a long-term goal. But it has many challenges to address at the general level.

- In India, the unemployment rate has continuously decreased from 5.72% in 2004 to 5.24% in 2019 (Table 2).

#### Table 2  Unemployment in India (2004–2019)

| Indicators                  | 2004  | 2009  | 2014  | 2019  |
|-----------------------------|-------|-------|-------|-------|
| Total unemployment rate (%) | 5.72  | 5.61  | 5.6   | 5.27  |
| Male                        | 5.72  | 5.59  | 5.6   | 5.28  |
| Female                      | 5.71  | 5.67  | 5.63  | 5.21  |

*Source: ILO Database*

\[
\text{UHCI (Full measure)} = \text{BER} \times \text{HCI} + (1 - \text{BER}) \times (\text{Minimum HCI})
\]

The world bank analyzed the HCI utilization measures for more than 160 countries and discovered that GDP per capita would be $\frac{1}{\text{UHCI}}$ higher in a sphere of complete utilization of education can improve health (Akyuz, 2017).

#### Fig. 1  Distribution of unemployed by level of education and sex in India in 2018 (Source: World Bank and ILO Database)
• Even though the female unemployment rate in India is higher compared to males, both values showed a decreasing trend from 2004 to 2019.

• In India, most females with an advanced level of education are unemployed and account for 24.68% of the aggregate population, and the male population has a percentage of 12.63 (Fig. 1).

• In the case of intermediate-level education, 16.2% of the female population and 9.95% of the population in India are unemployed.

• In the case of primary education in India, females are less unemployed, 2.9%, compared to males with, 4.4%.

• The report published by Statista Research Department (2021) revealed that graduate has the highest share of 16.3% of unemployment, and the budget estimates by the Indian government also say that there has been a deficit in the estimates of the actual number of jobs created compared to the real jobs created over the years.

**Human Capital Underutilization**

The unemployment rate is considered a measure of labor underutilization, but it has limited to a specific population ignoring those who are employed and those who are outside the labor force. The following are the four underutilization indicators introduced during the Nineteenth International Conference of Labor Statisticians (ICLS) (Gammarano & Mathys, 2018).

\[
LU_1 = \frac{\text{Unemployment}}{\text{Labour force}} \times 100
\]

\[
LU_2 = \frac{\text{Time – related underemployment} + \text{Unemployment}}{\text{Labour force}} \times 100
\]

Time-related underemployment can be defined as the category of employees who want to work for more hours if they have been allowed to work.

\[
LU_3 = \frac{\text{Unemployment} + \text{Potential labour force}}{\text{Labor force} + \text{Potential labour force}} \times 100
\]

The potential labor force is the category of the labor force in which they are actively searching for jobs or will enter the labor market shortly.

\[
LU_4 = \frac{\text{Time – related underemployment} + \text{Potential labour force}}{\text{Labor force} + \text{Potential labour force}} \times 100
\]

• The combined rate of time-related underemployment and unemployment in LU2 of India decreased from 8.9% in 2010 to 8.1% in 2019 (Table 3).
For LU2, we found that youth labor underutilization (15–24) LU2 was high 25.8% in 2019. It increased between 2010 and 2019 (from 24 to 25.8%). Youth labor underutilization was particularly high among young women. In 2019, female labor underutilization LU2 was 26.8%. However, it was 25.6% among males.

In terms of geographical coverage of disparities in labor underutilization, the rate in urban areas is higher than that of rural areas, and it accounts for 9% in urban areas and 7.7% in rural areas in 2019.

The combined rate of unemployment and potential labor force LU3 of India decreased from 6.8% in 2010 to 6.6% in 2020.

| Year | LU2 | LU3 | LU4 |
|------|-----|-----|-----|
| 2010 | 8.9 | 6.8 | 10  |
| 2011 | 8.8 | 6.8 | 9.9 |
| 2012 | 8.7 | 6.8 | 9.9 |
| 2013 | 8.7 | 6.9 | 9.9 |
| 2014 | 8.6 | 6.8 | 9.8 |
| 2015 | 8.5 | 6.8 | 9.7 |
| 2016 | 8.4 | 6.8 | 9.6 |
| 2017 | 8.3 | 6.7 | 9.5 |
| 2018 | 8.2 | 6.7 | 9.5 |
| 2019 | 8.1 | 6.6 | 9.4 |

Table 3  Labor underutilization in India (2010–2019)

Source: ILO Database
• In 2019, youth labor underutilization (15–24) was 27.1% for LU3. It grew between 2010 and 2019 (23.2 to 27.1%). Female youth labor underutilization was higher compared to male youth underutilization.
• In 2019, females had an LU2 of 29.2%, while males had an LU2 of 26.6%. We also discovered that the LU3 rate was low in the high age group (25+), with 3.2% in 2010 and 3% in 2019.
• The compound labor underutilization rate in LU4 decreased from 10% in 2010 to 9.4% in 2019.
• In terms of geographical coverage of disparities in labor underutilization, the rate in urban areas is higher than that of rural areas, and it accounts for 10.4% in urban areas and 8.9% in rural areas in 2019.
• The youth labor underutilization (15–24) LU4 in 2019 was 29.7% [31.4% for females and 29.4% for males].
• We also discovered that the LU4 rate was constant in the high age group (25+), with 6% in 2010 and 2019.
• LU4 for females was 8.4% in 2019 [13.4% in urban and 6.4% in rural], and the LU4 youth females increased from 28.3% in 2010 to 31.4 in 2019.

It is important to note that the economic growth in India fluctuates over time from 2005 to 2019 (Fig. 2). During 2008, the world witnessed the great depression, adversely affecting the Indian economy, and the GDP has crippled to 3.08%. After that, a remarkable recovery and a GDP hike to 7.86 in 2010. It remained stagnant in 2010 and again decreased to 5.24% in 2011. In 2016, real economic growth attained the highest values in 2010 and 2016 with a percentage of 8.49 and 8.25, respectively. After 2016, it showed a downward trend and reduced to 4.04% in 2019. It is due to various policy agendas of government, like demonetization of currency, tax reforms, and also to the collapse in private consumption.

Unemployment is considered an indicator of labor underutilization. In India, the unemployment rate was consistent during 2010–2011, then fluctuated through the years and showed a downward slope from 2015 to 2019. But as per the latest data of World Bank (2021), the unemployment rate in India increased to 7.11% in 2020, which is a record hike compared to the last decade. This is due to the outbreak of the COVID-19 pandemic, which also hurts the global economy. The unemployment of the total workforce in India was 5.27% in 2019, a lower percentage than the previous year. So it can be inferred that India was successfully implementing measures to abolish the unemployment scenario, which might be interrupted due to the outbreak of the COVID-19 pandemic.

Data and Methodology

The current study is based on the annual time series data from 2005 to 2019 and collected from secondary sources like the International Labor Organization (ILO) and the World Bank database. The applied econometric techniques like Augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test, Johansen Integration test for
Cointegration, and the Autoregressive Distributed Lag (ARDL) model were used to estimate the relationship between the human capital underutilization on economic growth and labor productivity in India.

**Unit Root Test**

The study incorporates the Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test to check the integration order of each variable, as used in the previous study of Nasrullah et al. (2021). The Augmented Dickey-Fuller (ADF) test by Dickey and Fuller (1979) is one of the commonly used unit root tests of time series data, and the Phillips-Perron (PP) test is an alternate model to test the unit root in the time series data was proposed by Phillips and Perron (1988).

**Johansen Test for Cointegration**

We have adopted the Johansen test for cointegration to find the robustness of the long-run association among the observed variables in the study (Johansen & Juselius, 1990).

**ARDL Bound Test for Cointegration**

The ARDL model for bound test for cointegration formulated by Pesaran et al. (2001) is used to find the presence long-run relationship between the observed variables in the ARDL model.

**ARDL Model**

The Autoregressive Distributed Lag Model (ARDL) is an ordinary least square (OLS)–based model, which uses the lags of dependent variables and the lagged values of independent variables, and it is applicable for non-stationary time series and for time series with mixed order of integration (Pesaran et al., 2001). By employing the ARDL model, the short-run and long-run effects can be directly and indirectly estimated respectively. Based on the objectives, the study proposes two ARDL models, ARDL (2, 1, 0, 1, 1) and ARDL (2, 1, 1, 1, 0), for estimating the relationship between human capital underutilization on economic growth and labor productivity respectively.

**Diagnostics Tests**

We have used three diagnostic tests for the estimated ARDL models: stability, serial correlation, and heteroscedasticity. To test the models’ stability, the cumulative sum of the recursive residuals (CUSUM) and CUSUM of squares proposed
by Brown et al. (1975) had performed. The Breusch-Godfrey Serial Correlation Lagrange Multiplier (LM) test proposed by Breusch and Pagan (1980) was used to check the autocorrelation of the residuals and heteroscedasticity tests such as by White test (White, 1980) and ARCH tests by Robert F. Engle (1982) were performed to verify the nature of variance in the estimated ARDL models.

**Empirical Results and Analysis**

**Unit Root Test**

The initial step is to determine whether the time series data are stationary or non-stationary or whether the time series data has a unit root. The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests were employed to check the stationarity of the observed time series data.

From Table 4, we can say that by using 0.05 level of significance, GDP is stationary at the level and first difference. At the same time, all other variables (UR, EAG, LP, and TU) are stationary at first difference.

Table 5 reveals that GDP and LP are stationary at the level and first difference, while all other variables (UR, EAG, and TU) are stationary at the first difference.

**Johansen Cointegration Test**

It is used to find the trace test and maximum Eigenvalue to find the robustness of the existence of the long-run relationship between the variables GDP, UR, EAG, LP, and TU.

### Table 4 Augmented Dickey-Fuller test

| Variable | Level Intercept | Intercept and trend | None | First difference Intercept | Intercept and trend | None |
|----------|----------------|---------------------|------|---------------------------|---------------------|------|
| GDP      | −3.102         | −2.998              | −0.974 | −4.313               | −4.110              | −4.426 |
|          | (0.049)*       | (0.016)*            | (0.029) | (0.006)**             | (0.032)*            | (0.000)*** |
| UR       | −2.624         | −2.873              | −0.808 | −4.358               | −4.184              | −4.470 |
|          | (0.111)        | (0.198)             | (0.347) | (0.006)**             | (0.029)*            | (0.000)*** |
| EAG      | −1.795         | −1.763              | 0.072  | −3.790               | −3.769              | −3.911 |
|          | (0.366)        | (0.667)             | (0.689) | (0.015)*             | (0.048)*            | (0.000)*** |
| LP       | −3.522         | −3.356              | −0.784 | −4.572               | −4.406              | −4.735 |
|          | (0.023)*       | (0.097)             | (0.358) | (0.004)**            | (0.020)*            | (0.000)*** |
| TU       | −0.097         | −1.654              | −5.261 | −3.412               | −9.536              | −1.455 |
|          | (0.931)        | (0.716)             | (0.000)*** | (0.032)*        | (0.000)***          | (0.000)*** |

Critical values of GDP at level are −3.102, −2.998, and −0.974 while at first difference −4.313, −4.110, and −4.426

*GDP* gross domestic product, *UR* unemployment rate, *EAG* employment in agriculture, *LP* labor productivity, *TU* time-related underemployment

* significant at 0.1; ** significant at 0.05; *** significant at 0.01
Table 6 shows the results of the Johansen test for the trace test and maximum Eigenvalue; the results reveal that at the 0.05 level of significance, there are two cointegrating eqn (s). So the findings confirm the presence of long-term relationship between those variables.

### Estimating the Relationship Between Human Capital Underutilization and Economic Growth

The dependent variable for the first objective is GDP.

#### ARDL Bound Test for Cointegration

ARDL bound test (Pesaran et al., 2001) is used to confirm the cointegration between the variables.

| Hypothesized no. of CE | Eigen value | Trace test | P-value ** | Max Eigen statistic | P-value ** |
|------------------------|-------------|------------|------------|---------------------|------------|
| None *                 | 0.99170     | 129.16     | 0.0000     | 67.089              | 0.0000     |
| At most 1 *            | 0.93177     | 62.074     | 0.0010     | 37.588              | 0.0011     |
| At most 2              | 0.73341     | 24.486     | 0.1865     | 18.508              | 0.1143     |
| At most 3              | 0.34057     | 5.9771     | 0.7012     | 5.8294              | 0.6404     |
| At most 4              | 0.010499    | 0.14776    | 0.7007     | 0.14776             | 0.7007     |

Trace and max Eigen value test indicates 1 cointegrating equation(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level; **MacKinnon-Haug-Michelis (1999) p-values
The cointegration test results indicate that the $F$-statistic value is 5.869218; it is greater than the lower bound and upper bound at 0.05 level of significance; it shows that there is a long-run equilibrium relationship between GDP (dependent variable) and labor productivity, time-related underemployment, employment in agriculture, and unemployment rate (independent variables) (Table 7).

The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests revealed that the variables are integrated in mixed order. Then, we can use the ARDL model.

### Table 7 $F$-bounds test

| Test statistic | Value | Significance | $I(0)$ | $I(1)$ |
|----------------|-------|--------------|--------|--------|
| $F$-statistic  | 5.869218 | 10%          | 2.45   | 3.52   |
| $k$            | 4     | 5%           | 2.86   | 4.01   |
|                |       | 2.5%         | 3.25   | 4.49   |
|                |       | 1%           | 3.74   | 5.06   |

Null hypothesis: No levels of relationship

### Table 8 ARDL model estimates for GDP

| Variable     | Coefficient | $t$-statistic | $P$-value** |
|--------------|-------------|---------------|-------------|
| GDP(−1)      | −0.574787   | −1.462811     | 0.2397      |
| GDP(−2)      | −0.313045   | −3.251823     | 0.0474      |
| LP           | 1.199969    | 16.94667      | 0.0004      |
| LP(−1)       | 0.650510    | 1.369039      | 0.2645      |
| TU           | 3.072639    | 1.659123      | 0.1957      |
| TU(−1)       | −3.202499   | −1.997912     | 0.1396      |
| EAG          | −0.120203   | −2.508106     | 0.0871      |
| EAG(−1)      | 0.085724    | 3.067444      | 0.0547      |
| UR           | −2.589599   | −1.825402     | 0.1654      |
| C            | 19.18778    | 3.865473      | 0.0306      |
| R-squared    | 0.995694    |               |             |
| Adjusted R-squared | 0.982778 |               |             |
| S.E. of regression | 0.220148 |               |             |
| Sum squared resid | 0.145395 |               |             |
| Log likelihood | 10.75992 |               |             |
| $F$-statistic | 77.08551   |               |             |
| Prob. ($F$-statistic) | 0.002173 |               |             |

Dependent variable—GDP, independent variables—labor productivity (LP), time-related underemployment (TU), employment in agriculture (EAG), and unemployment rate (UR)

** Represent 5% level of significance
ARDL (2, 1, 0, 1, 1) Model

The ARDL model estimates reveal that GDP is significantly positively affected by only labor productivity (LP). Over the long run, a 1% increase in LP leads to 1.19% increase in GDP, which is statistically significant at 0.05 level. Table 8 reveals that the GDP has a negative relationship with the unemployment rate (UR). Over the long run, a 1% decrease in UR will bring 2.58% increase in GDP, which is statistically insignificant at 0.05 level. Bhowmik (2016) also reported that the relationship between GDP and unemployment growth rate in India was insignificant during 1991–2014. The GDP has a negative relationship with the first lag of TU (0.1396), which is also greater than at 0.05 level. Over the long run, a 1% decrease in TU will bring 3.20% increase in GDP, which is statistically insignificant at 0.05 level. Suppose the employment in agriculture (EAG) decreased by 1%, the labor goes for the industry or service sector, which will increase GDP by 0.085%, but it is statistically insignificant at 0.05 level.

Table 9 shows the result of the ARDL long-run form and bounds test. It indicates that the labor productivity (LP) is the only variable with statistical significance as it lies in the cut-off of 0.05 level of significance. So it can be inferred that labor productivity has a significant positive relationship with GDP in the long run. In contrast, all the other variables have an insignificant negative relationship with GDP.

| Variable | Coefficient | t-statistic | P-value** |
|----------|-------------|-------------|-----------|
| LP       | 0.980214    | 17.84084    | 0.0004    |
| TU       | −0.068788   | −0.303025   | 0.7817    |
| EAG      | −0.018264   | −1.211863   | 0.3123    |
| UR       | −1.371732   | −1.518161   | 0.2263    |

Dependent variable—GDP, independent variables—labor productivity (LP), time-related underemployment (TU), employment in agriculture (EAG), and unemployment rate (UR)

** Represent 5% level of significance

Table 10 ECM regression for GDP

| Variable        | Coefficient | t-statistic | P-value** |
|-----------------|-------------|-------------|-----------|
| C               | 19.18778    | 8.282217    | 0.0037    |
| D(GDP(−1))      | 0.313045    | 6.268172    | 0.0082    |
| D(LP)           | 1.199969    | 37.80160    | 0.0000    |
| D(TU)           | 3.072639    | 4.455564    | 0.0210    |
| D(EAG)          | −0.120203   | −5.827519   | 0.0101    |
| CointEq(−1)     | −0.887832   | −8.274915   | 0.0037    |

Dependent variable—GDP, independent variables—labor productivity (LP), time-related underemployment (TU), employment in agriculture (EAG), and unemployment rate (UR)

** Represent 5% level of significance
Table 10 shows the short-run ARDL results of GDP on its independent variables. The value of cointegration is $-0.887832$. It is statistically significant and less than zero, which means that 88% of disequilibrium will be corrected moving from the short to the long run. The results also reveal no significant effect of the unemployment rate on GDP.

**Checking Stability**

The CUSUM and CUSUM of squares tests were used to check the stability and accuracy of the estimated ARDL models.

Figures 3 and 4 confirm that the estimated the ARDL model satisfies the stability condition because the CUSUM and CUSUM of squares are within the cut-off of 5% level, and there is no unit root outside the significance lines.

**Checking Serial Correlation and Heteroscedasticity**

Table 11 shows the $P$-value of 0.4089 for the Breusch-Godfrey Serial Correlation LM test, indicating no serial correlation. So the null hypothesis that there is no serial correlation is not rejected at 0.05 level of significance, which confirms no evidence of the serial correlation between errors in the estimated ARDL model. Table 15 also revealed that the errors of the estimated model have constant variance (i.e., no heteroscedasticity) as the $P$-value of White and ARCH tests (0.1462 and 0.4876) is greater than at 0.05 level of significance. So the null hypothesis of homoscedasticity is not rejected for the estimated ARDL model (2, 1, 0, 1, 1) model.
Estimating the Relationship Between Human Capital Underutilization and Labor Productivity

The dependent variable for the second objective is labor productivity (LP).

ARDL Bound Test for Cointegration

The test results indicate that the $F$-statistic value is 5.215421; it is greater than the lower bound and upper bound at 5% level of significance. It shows that there is a long-run equilibrium relationship between labor productivity (dependent variable) and GDP, time-related underemployment, employment in agriculture, and unemployment rate (independent variables) (Table 12).

ARDL (2, 1, 1, 1, 0) Model

The ARDL estimates show that labor productivity (LP) is significantly positively affected by GDP only. Over the long run, 1% increase in GDP leads to 0.88%
increase in LP which is statistically significant at 0.05 level. Table 13 reveals that LP has a negative relationship with the time-related underemployment. Over the long run, 1% decrease in TU leads to 3.77% increase in LP, which is statistically insignificant at 0.05 level. Also, the unemployment rate has no statistically significant effect on labor productivity.

Table 14 shows the result of the ARDL long-run form and bounds test. It indicates that GDP is the only variable with statistical significance as it lies in the cut-off of 0.05 level of significance, so it can be inferred that in the long run only GDP has a significant positive relationship with labor productivity, and all the other variables are not statistically significant in the long run.

| Table 12 | F-bound test |
|-----------|-------------|
| Test statistic | Value | Significance | I(0) | I(1) |
| F-statistic | 5.215421 | 10% | 2.45 | 3.52 |
| K | 4 | 5% | 2.86 | 4.01 |
| | | 2.5% | 3.25 | 4.49 |
| | | 1% | 3.74 | 5.06 |

Null hypothesis: no levels relationship

| Table 13 | ARDL model estimates for LP |
|-----------|-----------------------------|
| Variable | Coefficient | t-statistic | P-value ** |
| LP(-1) | -0.476146 | -1.006445 | 0.3883 |
| LP(-2) | 0.312322 | 2.544830 | 0.0843 |
| GDP | 0.888921 | 13.60152 | 0.0009 |
| GDP(-1) | 0.416650 | 1.080519 | 0.3590 |
| UR | 2.020132 | 1.499666 | 0.2307 |
| TU | -3.771755 | -2.119318 | 0.1243 |
| TU(-1) | 3.961483 | 2.459738 | 0.0909 |
| EAG | 0.091244 | 1.931530 | 0.1489 |
| EAG(-1) | -0.082174 | -2.746307 | 0.0710 |
| C | -15.76880 | -3.736593 | 0.0334 |
| R-squared | 0.995273 |
| Adjusted R-squared | 0.981093 |
| S.E. of regression | 0.219900 |
| Sum squared resid | 0.145068 |
| Log likelihood | 10.77456 |
| F-statistic | 70.18711 |
| Prob. (F-statistic) | 0.002497 |

Dependent variable—LP, independent variables—gross domestic product (GDP), time-related underemployment (TU), employment in agriculture (EAG), and unemployment rate (UR)

**Represent 5% level of significance
Table 14 ARDL long-run form and bounds test

| Variable       | Coefficient | t-statistic | P-value ** |
|----------------|-------------|-------------|------------|
| GDP            | 1.121794    | 9.132030    | 0.0028     |
| UR             | 1.735771    | 1.101096    | 0.3513     |
| TU             | 0.163021    | 0.442239    | 0.6883     |
| EAG            | 0.007793    | 0.311740    | 0.7756     |

Dependent variable—LP, independent variables—gross domestic product (GDP), unemployment rate (UR), time-related underemployment (TU), and employment in agriculture (EAG)

** Represent 5% level of significance

Table 15 shows the short-run ARDL labor productivity results on its independent variables. The value of cointegration is −0.63824. It is statistically significant and less than zero, which means that 63% of disequilibrium will be corrected moving from the short to the long run. In the short run, time-related underemployment has a significant negative relationship with LP.

Checking Stability

The result of CUSUM and CUSUM of squares are as follows:

Figures 5 and 6 confirm that the estimated the ARDL model satisfies the stability condition because the CUSUM and CUSUM of squares are within the cut-off of 5% level, and there is no unit root outside the significance lines.

Table 16 shows the P-value of 0.9981 for the Breusch-Godfrey Serial Correlation LM test, indicating no serial correlation. So the null hypothesis that there is no serial correlation is not rejected at 0.05 level of significance, which confirms no evidence of the serial correlation between errors in the estimated ARDL model. Table 16 also reveals that the errors of the estimated model have constant variance (i.e., no heteroscedasticity) as the P-value of White and ARCH tests (0.2022 and 0.6999) is greater than at 0.05 level of significance. So the null hypothesis of homoscedasticity is not rejected for the estimated ARDL (2, 1, 1, 1, 0) model.

Table 15 ECM regression for LP

| Variable       | Coefficient | t-statistic | P-value ** |
|----------------|-------------|-------------|------------|
| C              | −15.76880   | −7.845742   | 0.0043     |
| D(LP(−1))      | −0.312322   | −6.047508   | 0.0091     |
| D(GDP)         | 0.888921    | 39.38601    | 0.0000     |
| D(TU)          | −3.771755   | −4.482832   | 0.0207     |
| D(EAG)         | 0.091244    | 4.887251    | 0.0164     |
| CointEq(−1)    | −0.63824    | −7.800422   | 0.0044     |

Dependent variable—LP, independent variables—gross domestic product (GDP), time-related underemployment (TU), employment in agriculture (EAG), and unemployment rate (UR)

** Represent 5% level of significance
Fig. 5 CUSUM stability test of ARDL model

Fig. 6 CUSUM of squares stability test of ARDL model. Selected model—ARDL (2, 1, 1, 1, 0), dependent variable—labor productivity (LP)

Table 16 Serial correlation and heteroscedasticity tests

| Tests                                      | Chi-squared value | P-value |
|--------------------------------------------|-------------------|---------|
| Breusch-Godfrey serial correlation LM test | 0.9965            | 0.9981  |
| White test heteroskedasticity              | 0.2300            | 0.2022  |
| ARCH test for heteroskedasticity           | 0.6718            | 0.6999  |

Dependent variable—labor productivity (LP), null hypothesis of serial correlation—no serial correlation, null hypothesis of heteroscedasticity—the variance for the errors are equal (homoscedasticity)
Conclusion and Policy Recommendations

Human capital underutilization arises when a labor market fails to explore the idle potential of the workforce, which would consequently affect an economy through the loss of aggregate output and the falling government revenue. It can be restrained by government intervention through specific policies and measures reducing the rate of unemployment and time-related underemployment.

The present study examined the effects of human capital underutilization on India’s economic growth and labor productivity. The ARDL results revealed that the unemployment rate has a negative but statistically insignificant relationship with GDP in the long run. Bhowmik (2016) also reported the insignificant relationship between GDP and the unemployment growth rate in India. The study also proved the long-run negative relationship between GDP and time-related underemployment in India, which is statistically insignificant. Furthermore, we found that time-related underemployment has a statistically significant negative relationship with labor productivity in the short run. The ARDL estimation indicates that a decrease in the rate of time-related underemployment will bring 3.77% increase in labor productivity in the short run. So, giving sufficient working hours to the active labor force will bring more labor productivity.

These findings suggest that the optimum utilization of human capital could foster economic growth and labor productivity in India. Being a country with an abundant source of demographic dividend, generating sufficient skill-oriented job opportunities for the current and potential labor force and imparting proper training to the existing labor force is a feasible alternative for the optimum utilization of human capital. The findings also recommend that the policymakers consider human capital utilization measures from the perspective of both individuals and the economy, which should be addressed in their policy framework.

Scholars may consider the comparative cross-country analysis of the various macro and microeconomic determinants of human capital underutilization for further research. Such studies will provide a global perspective and cross-country insights into factors influencing human capital underutilization.

Data Availability  The data will be provided on demand.

References

Aggarwal, S. C., Satija, D., & Khan, S. (2019). Inclusive growth in India - Learning from best practices of selected countries (Issue 375).

Akyuz, Y. (2017). Global economic prospects. In The Financial Crisis and the Global South (issue June). https://doi.org/10.2307/j.ctt183pb3w.5

Al-Habees, M. A., & Runman, M. A. (2012). The relationship between unemployment and economic growth in Jordan and some Arab countries. World Applied Sciences Journal, 18(5), 673–680. https://doi.org/10.5829/idosi.wasj.2012.18.05.16712

Anand, R., Tulin, V., & Kumar, N. (2014). India: Defining and explaining inclusive growth and poverty reduction. In IMF Working Papers (Vol. 14, Issue 63). https://doi.org/10.5089/9781484354230.001

Andrei, D., Vasile, D., & Adrian, E. (2009). The correlation between unemployment and real GDP growth. A study case on Romania. Annals of Faculty of Economics, 2.1, 317–322.
Ball, L. M., Leigh, D., Loungani, P., & Al., E. (2013). Okun’s Law: Fit at 50? In *IMF Working Papers* (Vol. 13, Issue 10). https://doi.org/10.5089/9781475574265.001

Barro, R. J. (1991). Economic growth in a cross section of countries. *Quarterly Journal of Economics, 106*(2), 407–443. https://doi.org/10.2307/2937943

Barro, R. J. (2001). Human capital and growth. *The American Economic Review, 91*(2), 12–17.

Bhat, T. A. (2019). The validity of Okun’s Law: Evidences from Indian economy. *Theoretical and Applied Economics, XXV, I*(4), 273–278.

Bhowmik, D. (2016). Relation between GDP growth rate and unemployment growth rate in India since the reform period. *Prestige International Journal of Management & IT - Sanchayan, 05*(01), 83–100. https://doi.org/10.37922/pijmit.2016.v05i01.008

Breusch, T. S., & Pagan, A. R. (1980). The Lagrange multiplier test and its applications to model specification in econometrics. *The Review of Economic Studies, 47*(1), 239. https://doi.org/10.2307/2297111

Brown, R. L., Durbin, J., & Evans, J. M. (1975). Techniques for testing the constancy of regression relationships over time. *Journal of the Royal Statistical Society: Series B (methodological), 37*(2), 149–163. https://doi.org/10.1111/j.2517-6161.1975.tb01532.x

Bhowmik, D. (2016). Relation between GDP growth rate and unemployment growth rate in India since the reform period. *Prestige International Journal of Management & IT - Sanchayan, 05*(01), 83–100. https://doi.org/10.37922/pijmit.2016.v05i01.008

BusinessToday. (2017). India facing problem of severe under-employment, says Niti Aayog. Retrieved September 23, 2022, from https://www.businesstoday.in/latest/economy-politics/story/india-facing-problem-of-severe-under-employment-says-niti-aayog-83379-2017-08-27

Cadil, J., Petkovova, L., & Blatna, D. (2014). Human capital, economic structure and growth. *Procedia Economics and Finance, 12*(March), 85–92. https://doi.org/10.1016/s2212-5671(14)00323-2

Chand, K., Tiwari, R., & Phuyal, M. (2018). Economic growth and unemployment rate: An empirical study of Indian economy. *PRAGATI : Journal of Indian Economy, 4*(02). https://doi.org/10.17492/pragati.v4i02.11468

Conteh, K. (2021). Economic growth and unemployment: An empirical assessment of Okun’s law in the case of Liberia. SSRN Electronic Journal, May. https://doi.org/10.2139/ssrn.3864474

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of American Statistical Association, 76*(366a), 427–431. https://doi.org/10.1080/01621459.1979.10482531

Doppelt, R. (2019). Skill flows: A theory of human capital and unemployment. *Review of Economic Dynamics, 31*, 84–122. https://doi.org/10.1016/j.red.2018.12.004

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica, 50*(4), 987–1007.

Gammarano, R., & Mathys, Q. (2018). *Spotlight on work statistics: Avoiding unemployment is not enough* (Issue August). Retrieved August 2, 2021, from https://www.ilo.org/global/statistics-and-databases/publications/WCMS_644467/lang--en/index.htm

Glyde, G. P. (1975). *Underemployment: Definition, causes, and measurement.*

Grant, C. (2017). *The contribution of education to economic growth: Evidence from Nepal.* https://doi.org/10.20472/iae.2016.023.032

Greenwood, A. M. (1999). International definitions and prospects of Underemployment Statistics. *Proceedings for the Seminario Sobre Subempleo, Bogota*, 1–18. Retrieved November 5, 2021, from http://files/799/wcms_087487.pdf

Gupta, P., & Blum, F. (2018). *India’s remarkably robust and resilient growth story.* World Bank Blog Page. Retrieved September 23, 2022, from https://blogs.worldbank.org/endpovertyinsou thisia/indias-s-remarkably-robust-and-resilient-growth-story

Hashem, E. A. (2021). The impact of human capital underutilization on productivity and economic growth in Egypt. *Journal of Economics and Business, 4*(2), 231–244. https://doi.org/10.31014/aib.1992.04.02.359

Hashmi, S. M., Khushik, A. G., Gilal, M. A., & Yongliang, Z. (2021). The impact of GDP and its expenditure components on unemployment within BRICS countries: Evidence of Okun’s law from aggregate and disaggregated approaches. *SAGE Open, 11*(2). https://doi.org/10.1177/21582440211023423

Helliwell, J. F. (2001). The contribution of human and social capital to sustained economic growth. In *OECD*. Retrieved September 23, from, http://www.oecd.org/innovation/research/1825902.pdf

Hjazeen, H., Seraj, M., & Ozdeser, H. (2021). The nexus between the economic growth and unemployment in Jordan. *Future Business Journal, 7*(1), 1–8. https://doi.org/10.1108/s43093-021-00088-3

Johansen, S., & Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration—With application to the demand for money. *Oxford Bulletin of Economics and Statistics, 52*(2), 169–210.
Khalid, W. (2021). The relationship between unemployment and economic growth in South Africa: VAR Analysis. *Forman Journal of Economic Studies, 17*(01), 1–32. https://doi.org/10.32368/fjes.20211701

Kim, J., Yoon, J. C., & Jei, S. Y. (2020). An empirical analysis of Okun’s laws in ASEAN using time-varying parameter model. *Physica A: Statistical Mechanics and Its Applications, 540*, 123068. https://doi.org/10.1016/j.physa.2019.123068

Kitov, I. O. (2021). The link between unemployment and real economic growth in developed countries. *SSRN Electronic Journal, 2011*. https://doi.org/10.2139/ssrn.3776796

Kukreja, M. (2013). Education as an integral part of human capital formation in India. *International Journal of Scientific & Engineering Research, 4*(March 2013), 3.

Levine, L. (2013). CRS report for congress economic growth and the unemployment rate. *Specialist in Labor Economics*, 1–10.

Lucas, R. E. (1988). On the mechanics of economic development. *Journal of Monetary Economics, 22*(1), 3–42. https://doi.org/10.1016/0304-3932(88)90168-7

Mankiw, Gregory, N., Romer, D., & Weil, D. N. (1992). A contribution to the empirics of economic growth. *Quarterly Journal of Economics, 107*(2), 407–437. https://doi.org/10.2307/2118477

Mathai, K., Duenwald, C., & Guschina, A. (2020). Social spending for inclusive growth in the Middle East and Central Asia. In *International Monetary Fund* (Issue 20).

Mimi, M. B., Haque, A. U., & Kibria, G. (2022). Does human capital investment influence unemployment rate in Bangladesh: A fresh analysis. *National Accounting Review, 4*(July), 273–286. https://doi.org/10.3934/NAR.2022016

Ministry of Finance. (2016). Structural changes in India’s labour markets. In *Economic Survey 2015–16*.

Nasrullah, M., Rizwanullah, M., Yu, X., Jo, H., Sohail, M. T., & Liang, L. (2021). Autoregressive distributed lag (ARDL) approach to study the impact of climate change and other factors on rice production in South Korea. *Journal of Water and Climate Change, 12*(6), 2256–2270. https://doi.org/10.2166/wcc.2021.030

Nauriyal, D. K., Sahoo, B. K., & Dixit, A. (2009). Economic growth, globalisation and human capital: Empirical evidence from India. *The Indian Economic Journal, 56*(4), 37–54. https://doi.org/10.1177/0019466220090404

Padders, A. H., & Mathavan, B. (2021). The relationship between unemployment and economic growth in India: Granger causality approach. *NVEO-Natural Volatiles & Essential Oils Journal, 8*(4), 1265–1271. https://doi.org/10.32368/fjes.20211701

Pelinescu, E. (2015). The impact of human capital on economic growth. *Procedia Economics and Finance, 22*, 184–190. https://doi.org/10.1016/s2212-5671(15)00258-0

Pennings, S. (2020). The utilization-adjusted Human Capital Index (UHCI) (Issue September).

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics, 16*(3), 289–326. https://doi.org/10.1002/jeae.616

Phillips, P. C. B., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika, 75*(2), 335–381. http://finpko.faculty.ku.edu/nyssi/FIN938/Phillips%26Perron_Biometrika_1988_UnitRootTest.pdf

Prachowny, M. F. J. (1993). Okun’s law: Theoretical foundations and revised estimates. *Review of Economics and Statistics, 75*(2), 331–336.

Rodriguez Hernandez, J. E. (2018). Factors determining labor underutilization in Spain by gender before and after the economic crisis. *Economic and Industrial Democracy, 42*(1), 92–115. https://doi.org/10.1177/0143831X17752266

Sackey, H. A., & Osei, B. (2006). Human resource underutilization in an era of poverty reduction: An analysis of unemployment and underemployment in Ghana. *African Development Review, 18*(2), 221–247. https://doi.org/10.1111/j.1467-8268.2006.00140.x

Samiullah. (2014). Relationship between unemployment and human capital. *Journal of Resources Development and Management, 3*, 1–11.

Sarbu, O., & Cimpoies, L. (2020). Labor force underutilization as a social and economic problem in Moldova. *Scientific Papers Series Management, Economic Engineering in Agriculture and Rural Development, 20*(1), 539–548.
Schundeln, M., & Playforth, J. (2014). Private versus social returns to human capital: Education and economic growth in India. *European Economic Review, 66*, 266–283. https://doi.org/10.1016/j.euroecorev.2013.08.011

Self, S., & Grabowski, R. (2004). Does education at all levels cause growth? India, a case study. *Economics of Education Review, 23*(1), 47–55. https://doi.org/10.1016/S0272-7757(03)00045-1

Shukla, S. (2017). Human capital and economic growth in India. *INTERNATIONAL JOURNAL OF CURRENT RESEARCH, 9*(11), 61628–61631. https://doi.org/10.30541/v44iipp.455-478

Statista. (2022). India - Distribution of gross domestic product (GDP) across economic sectors 2021. Retrieved September 26, 2022, from https://www.statista.com/statistics/271329/distribution-of-gross-domestic-product-gdp-across-economic-sectors-in-india/

Statista Research Department. (2021). India - unemployment rate by education level 2019 | Statista. Statista Research Department. Retrieved July 28, 2021, from https://www.statista.com/statistics/1001039/india-unemployment-rate-by-education-level/

Tsamadias, C., & Prontzas, P. (2012). The effect of education on economic growth in Greece over the 1960–2000 period. *Education Economics, 20*(5), 522–537. https://doi.org/10.1080/09645292.2011.557906

Union of International Associations. (1997). Underutilization of human resources. The Encyclopedia of World Problems & Human Potential. Retrieved October 17, 2022, from http://encyclopedia.uia.org/en/problem/137000

Viswanath, J., Reddy, K. L. N., & Pandit, V. (2009). Human capital contributions to economic growth in India: An aggregate production function analysis. *Indian Journal of Industrial Relations, 44*(3), 473–486.

Wilson, R. A., & Briscoe, G. (2004). The impact of human capital on economic growth: A review. *Impact of Education and Training, 54*, 1–64. Retrieved September 23, 2022, from https://www.cedefop.europa.eu/files/BgR3_Wilson.pdf

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica, 48*(4), 817–838.

World Bank. (2020). *Human Capital Index 2020 -India* (Issue October). Retrieved July 28, 2021, from https://databank.worldbank.org/data/download/hci/HCI_2pager_IND.pdf?cid=GGH_e_hcpxternal_en_ext

World Bank. (2021). *GDP growth (annual %) - India* | Data. Retrieved August 2, 2021, from https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG?end=2020&locations=IN&start=1991

World Bank Group. (2020). Covid-19 and Human Capital. In *World Development Report 2019: The Changing Nature of Work* (pp. 1–57).

Xia, X. (2021). Unemployment, inflation and impact of GDP in India. *Advances in Economics, Business and Management Research, 166*, 641–647. https://doi.org/10.2991/aebmr.k.210319.118

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.