The Technology-Inequality Nexus in India: Long-Term Evidence for Policy and Sustainable Development

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Abstract
In this study, technological advancement and its influence on income inequality in India are examined over the period 2004–2024, which was marked by rapid digital expansion, increased investment in research and development, and substantial structural transformation within the economy. The analysis uses time-series data in annual frequency and ties the Autoregressive Distributed Lag (ARDL) approach to examine both long-run and short-run movements among the variables. Income inequality is measured with the Gini index from the SWIID database, while technological advancement is captured through gross domestic expenditure on R&D as a share of GDP. Education, reflected by the share of people with at least secondary schooling, and real GDP per capita growth are added as core controls. A post-2020 dummy accounts for the disruption caused by the COVID-19 shock. The results show that technological progress has increased inequality in both the short run and long run, which is broadly consistent with the pattern of skill-biased technological change observed in many developing economies. Education works in the opposite direction and helps in reducing inequality, showing that human capital continues to play a strong equalising role. Economic growth has a mild but positive effect on inequality, raising concerns about the inclusiveness of India's growth path. The Toda–Yamamoto causality test supports a one-way causal effect running from technology and education to inequality. The study adds to the recent literature by combining ARDL estimates with Toda–Yamamoto causality within a single time-series setting and by placing India's experience within the wider debate on sustainable and inclusive development. The use of a structural-break dummy for the post-pandemic period allows the paper to capture how technological and educational channels behaved during a major shock. The results show that India needs to improve access to digital technologies for all sections of society. increase investment in education and skill development and introduce labour policies that support Low-Skilled workers. Without these efforts, the benefits of technological progress may not reach poorer and disadvantaged groups, and inequality could continue to increase.

Keywords: Technological Change; Income Inequality; ARDL; Structural Break; Education; India; Toda–Yamamoto

1. INTRODUCTION

Income inequality continues to be a serious concern for developing economies, particularly those Undergoing rapid technological advancement and structural transformation. India represents an important example, where the expansion of digital technologies and innovation has significantly influenced production systems; employment patterns; and access to economic and social services. Although these changes have contributed to sustained economic growth, they have also raised important questions about whether the gains from technological progress are distributed evenly across different segments of society. Existing evidence suggests that, in the absence of strong education and skill development policies, the diffusion of digital technologies in emerging economies can increase disparities between skilled and unskilled workers, as well as between formal and informal sectors (UNDP, 2023; ILO, 2022). This highlight the need to examine the Distributional impact of technological progress in India over the past two decades.

Since the mid-2000s, India's Economic Development has been closely linked with rising investment in research and development, the rapid growth of information & communication technologies, and policy reforms aimed at expanding digital infrastructure and accessibility (OECD, 2022; World Bank, 2023). Government initiatives such as Digital India, Aadhaar-enabled service delivery, and policies promoting innovation and entrepreneurship have transformed business operations and increased the demand for skilled labour. At the same time, several studies and reports indicate that income inequality has widened, with the benefits of technological change largely concentrated among high-skilled workers, urban populations, and capital-intensive industries (Oxfam, 2022; Jha & Verma, 2021). The COVID-19 pandemic further intensified these inequalities as informal workers, Migrant labourers, and economically vulnerable households experienced disproportionate economic hardship (CMIE, 2021; IMF, 2022). These developments make the period from 2004 to 2024 particularly relevant for analysing the relationship between technological progress and Income Inequality in India.

Though the problem has drawn an increasing number of scholarly interests, there are limited empirical investigations which examine how the technological development directly affects inequality in the context of India. The literature in the field is dominated by the broad understanding of the nexus between economic growth and inequality or deals with labour market reforms without tracking down to the particular impact of technological signals like research and development spending in a time-series context. Besides, most studies do not adequately consider structural shocks, especially the COVID-19 pandemic that significantly changed the structure of employment and accelerated the rate at which people started using digital technologies. Another gap is in the way of detailed research that simultaneously evaluates both long-term and short-term associations and empirically experiments on the causality of technological development and inequality. It is in these areas that this research aims to fill this gap by examining the role of technological development in increasing the level of income inequality in India, and the role of mitigating factors, including education and economic growth, can mitigate or reverse this impact.

The analysis is designed to be based on three main objectives. To assess it, it measures the long and the short-run impact of technological advancement on income inequality in India through the Autoregressive Distributed Lag (ARDL) modelling technique. Second, it examines the role of education and economic growth as inhibitory or supporting factors in the construction of inequality. Third, it discusses the causality of the direction of the technology development and inequality by using TodaYamamoto causality testing framework. Besides that, the study captures the drivers of inequalities in the aftermath of a significant economic shock by adding a structural-break dummy variable to the period after 2020.

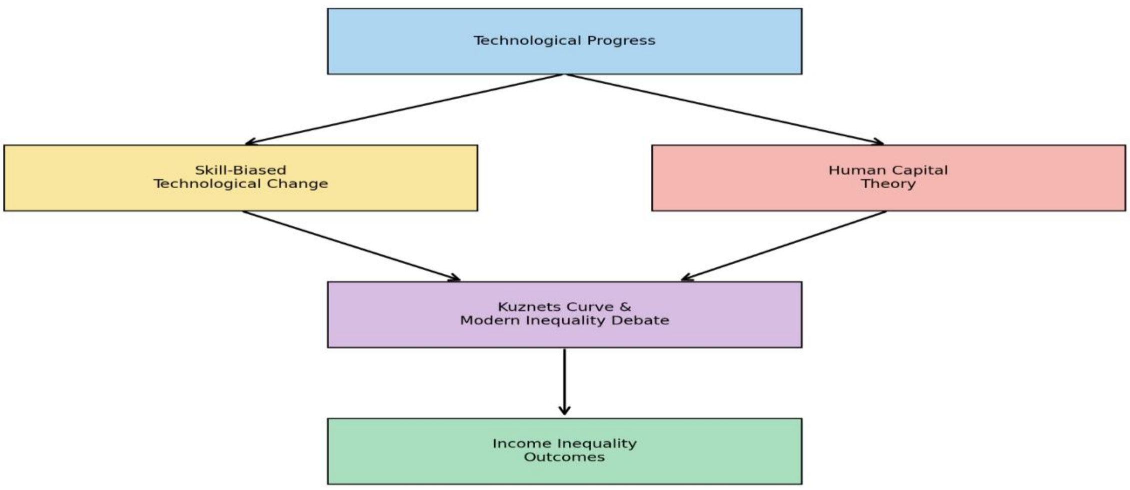
This study has its contribution in its thorough approach in terms of methodology. It combines ARDL estimation, structural-break analysis, and Toda-Yamamoto causality testing into a time series framework- a methodology which has not been used extensively in the past to analyze dynamics of inequality in India. In addition, the paper places technological advances in a wider development scenario in terms of evaluating the effect of technological advances on inclusive and sustainable economic growth. This view is relevant especially at the time when policy discussions are taking place on how to attain equitable development results in rising economies (UNCTAD, 2023; ESCAP, 2022).

The remainder of the paper is organised as follows. Section 2 presents a review of the theoretical and empirical literature on the relationship between technological advancement and income inequality, with emphasis on developing economies, Section 3 describes the data sources, variable definitions, and econometric methodology, Section 4 discusses the empirical results. Section 5 provides the conclusion, and Section 6 outlines the limitations of the study and suggests directions for future research.

2. LITERATURE REVIEW

Theoretical Underpinnings

Figure 1. Theoretical Linkages Between Technological Progress and Income Inequality



Note: The diagram illustrates how Technological Progress interacts with major theoretical channels shape Income-Inequality outcomes in developing economies such as india.

The association between income inequality and technological progress has traditionally been at the centre of study in development economics and in labour economics. The Skill-Biased Technological Change (SBTC) hypothesis presents one of the most powerful explanations. This paradigm proposes that technological changes are likely to cause a rise in the need of skilled labor and a decrease in the use of routine and low-skill activities. Consequently, wage disparities are increased and jobs become skewed (Acemoglu, 2002; Autor, 2019). In more and more digitally produced and automated economies, the process frequently becomes an increase in incomes earned by the educated population, accompanied by a stagnation in the opportunities of those with fewer formal competences, or a downward trend thereof.

The Human Capital Theory reinforces this premise by highlighting the significance of education and training so that workers can be able to respond to changes in technology. Becker (1993) emphasizes that investment in schooling and skill formation makes people more productive and allows workers to better adapt to technological change. Recent empirical findings suggest that it is observed that countries with broader and more substantial access to education also have a more moderate growth of inequality when violence is high in times of accelerated technological change (OECD, 2021; World Bank, 2023). In this model, human capital effectively acts as a buffer system, so workers are displaced and they enter into more productive and high-tech sectors.

Classical development theory can also provide insights. The inverted-U hypothesis of Kuznets (1955) suggests that the level of income inequality is at first increasing in the first stages of structural change because labour moves to the modern sectors, but later plateaus once the economies reach a level of maturity, and the gains become widely distributed. Nevertheless, the modern world of scholarship doubts the necessity of such a path in the digital age. According to Piketty (2014), technological change, especially in digital and capital-intensive jobs, has strengthened the concentration of capital income, and improvements in wages to lower-skilled labour have been relatively weak. This trend is seen in a number of developing countries, where informal jobs are very common and digital access is distributed unevenly (UNDP, 2023; ESCAP, 2022).

A summation of these theoretical views suggests that technological development does not necessarily contribute to either increased or reduced equality. Its distributional implications are heavily reliant on national policy decisions, especially concerning education, labour-market adjustment policies, and the inclusive nature of technological diffusion. The relationship between technological progress and income inequality in an Indian context, where pursued by sheer disparities in skills, regional imbalance, and large informal-based workforce, is most probably going to be complex and heavily reliant on policy interventions.

Empirical Literature Review

International Evidence:

Empirical studies of the world reveal that the correlation between technological progress and income inequality is significantly different in each country conditioned by the rate of human capital formation and the intensity of digital penetration. Aghion et al. (2019) show that innovation based growth can reinforce income inequality in those economies in which advances in education and skill development fail to match with technological transformation. Newer data also suggest that digital transformation is a driver of expanding wage differentials by raising the relative excellence of skilled labour and decreasing chances of low skilled labour (Hong, 2024; Nogueira, 2023). Surveys regarding emerging economies also indicate that technological advancements tend to benefit urban residents and skilled laborers more severely, unless backed by mass investment in training, education, and digital literacy (Zhang, 2025; Ho, 2025).

There is also a considerable amount of international research focused on the relevance of digital divide in predetermining inequality outcomes. Internet connectivity and access to and use of digital infrastructure and technological capabilities may contribute to reinforcing existing economic and social inequalities (Nayyar, 2024). The same tendencies are noticed in the economies of Asia, where the speed of technological adoption has resulted in increased inequality in the areas with a lack of educational systems and institutional back-up (Zhuang et al., 2014). The cross-country studies have shown that technological advances are associated with rising levels of inequality in case redistributive policies and state investment in education and social infrastructure are inadequate (Chan, 2022; Madsen, 2024).

In terms of methodologies, recent international research is almost entirely based on time-series models as well as panel ARDL models to investigate the dynamics of inequality. These methods allow researchers to evaluate long-run equilibrium relationships as well as including tests of short-run adjustments in addition to testing causality. These approaches come in especially handy in countries experiencing structural changes and little data, which would enable greater insight into the dynamics of the interaction of technological advancement, education, financial development, and inequality over time.

Evidence from India:

Empirical evidence from 1ndia indicates that income inequality has increased alongside periods of technological advancement and structural transformation. Laskar (2023) found that differences in digital access across 1ndian states have contributed to widening Income Disparities. Similarly, Oxfam (2022) reports that digital infrastructure and online platforms have disproportionately benefited urban populations and skilled workers, while rural and low-skilled groups have experienced relatively limited gains. Earlier research emphasises that structural characteristics of India's labour market that includes the large informal sector, restricted labour mobility, and uneven distribution of skills have amplified the unequal effects of technological change (Jha & Verma, 2021; Mehrotra & Parida, 2021).

Several studies also examined the interaction between technological progress, education, and inequality within the Indian context. Chaudhuri and Gupta (2020) show that regions with higher levels of secondary education experience smaller increases in inequality during periods of technological change, highlighting the important role of human capital in reducing inequality. Other empirical studies using ARDL and related Econometric Techniques suggest that technological advancement, economic openness, and structural shifts have contributed to rising inequality in both the short run and long run (Rout, 2022; Goel et al., 2021).

Recent historical analyses further reveal a significant rise in income and wealth concentration in India, particularly after 2010. Chancel et al. (2024) document that gains from capital-intensive and technology-driven sectors have been concentrated among a relatively small segment of the population. These findings suggest that technological progress alone is insufficient to reduce inequality unless accompanied by inclusive economic policies, stronger education systems, and effective social protection measures.

Despite the growing body of literature, important gaps remain. Only a 1imited number of studies use a comprehensive time-series framework to analyse the joint impact of Technological Advancement, Education, and Economic growth on 1nequality in India. Moreover, very few studies incorporate structural breaks such as the COVID-19 pandemic, which significantly disrupted Labour markets, digital access, and educational continuity. Evidence on causal relationships using advanced econometric techniques such as the TodaYamamoto approach also remains scarce.

Identified Research Gaps:

Despite the useful information in the previous studies, some of the problems have not been resolved particularly in the setting of developing economies like India. To begin with, the vast majority of international research is based on cross-country or panel data, and, therefore, it is not possible to observe much country-specific dynamics and structural transformations. There are relatively few studies that conduct time-series analyses that are devoted to particular economies.

Second, much of the empirical research on India tends to study inequality in conjunction with economic growth, labour markets or structural reforms, but very little empirical research directly investigates technological advancement through the application of variables that can be measured by use of indicators like expenditure on research and development. Moreover, the existing literature seldom combines the technology development, education, and economical development under the homogenous empirical model.

Third, recent changes in structure in India, especially the fast-growing digital technologies since 2016, have not been adequately studied with the help of current empirical data. Another significant structural break that had significant impacts on technological adoption, labour mobility, and education access is the COVID -19 pandemic. Nevertheless, such types of disruption are not explicitly considered in most empirical studies.

Fourth, there is a little empirical data on causal relationships among technological advancement, education, growth of the economy, and inequality in India. The overwhelming number of studies pays attention only to long-run relationships or correlations without the use of higher level causality-testing methods including Toda-Yamamoto procedure, which is especially applicable on time series data with mixed integration characteristics.

Lastly, none of the existing literature thoroughly analyse the short-run dynamics, long-run equilibrium relationships, and causal interactions in one time-series framework along with having structural disruption. This is a massive gap in the interpretation of the effects of technological sophistication in the economic growth of a swiftly computerizing economy in terms of income inequality.

The current paper will deal with these weaknesses with the application of annual time-series data (20042023) and an ARDL bounds-testing framework and structural break Dummy to the results to represent post-pandemic impacts. Furthermore, the Toda- Yamamoto causality method is adopted in order to investigate the directionality of causality. This unified approach to researching the topic offers a more thorough and valid analysis of the connection between technological advancement and income disparity in India in the times of stability and in times of structural disturbance.

3. DATA AND METHODOLOGY

The paper uses annual time-series data on India between the years 2004 and 2024. The period is a pivotal point in the economic development of the country, being marked by the rapid digitalisation and the evolution of the market-oriented reforms with an even bigger focus on the shift toward the technological foundation of the production process. In this era, India was experiencing tremendous increase in internet connectivity, angering utilization of information and communication technology, and an escalation in the extent of public and private research and development investment. These structural changes are what render this period quite appropriate when it comes to examining how technological advancements have influenced income inequality in a big and fast developing emerging economy.

The major concern of this analysis is to check whether the technological improvement generated a decrease in income inequality or rather created increase in the income disparities. Income inequality is defined and is included as the dependent variable, and it is determined by the Gini coefficient, where consumption-adjusted income data were taken by the Standardised World Income Inequality Database (SWIID). The SWIID data set is also known to offer superior and steady inequality estimates among nations and across time, which makes it a good tool of long-term time-series analysis.

The most important explanatory variable in the given study is technological advancement. It is quantified by gross domestic spending on research and development as a percentage of the GDP. This indicator shows how much a country invests in innovation and how more technology becomes significant in the formation of economic activity. The data of this variable are derived at the world development indicators database.

Moreover, to reflect broader structural effects on the inequality of incomes, two control variables are involved. The former is education, which is expressed by the percentage of population with at least secondary education level. This variable means the amount of human capital in the economy and its adaptability to technological change. The economic growth is the second control variable but this is in the form of the annual growth rate of the real GDP per capita. This is a variable that is added to explain how the general economic performance influences income distribution. The two variables are widely applied both in the theoretical and empirical research concerning the determinants of inequality in developing economies.

The decision to follow the established economic theory is informed by the recent empirical studies that focus on the focus of the roles of technological advancement, human capital, and economic growth to influence the income distribution.A comprehensive description of all variables, along with their definitions and data sources, is provided in Appendix Table A1.

Model Specification

We postulate the following linear model to analyze the long-run relationship between technological progress and income inequality:

$$\mathrm{GINI}_t = \alpha_0 + \alpha_1 \mathrm{TECH}_t + \alpha_2 \mathrm{EDU}_t + \alpha_3 \mathrm{GRW}_t + \alpha_4 \mathrm{DUM2020}_t + \varepsilon_t$$

Where: GINI_t is the Gini coefficient (income inequality); TECH_t is the R&D expenditure (% of GDP); EDU_t is the Population with secondary education; GRW_t is the GDP per capita growth; $\mathrm{DUM2020}_t$ is the Structural dummy variable (1 for 2020–2024 , 0 otherwise and ε_t is the error term. Also, $\alpha_0, \alpha_1, \alpha_2, \alpha_{3,}$ and α_4 are the parameters to be estimated This specification captures the influence of technological change and socio-economic control factors on inequality.

Time Series Properties and Stationarity Tests

To ensure that the model does not suffer from spurious regression problems, we perform the Augmented Dickey-Fuller (ADF) unit root test for all variables. T

$$\Delta Y_t = \gamma Y_{t-1} + \sum_{i=1}^{k} \delta_i \Delta Y_{t-i} + \mu + \varepsilon_t$$

Where Y_t is the variable being tested; ΔY_t denotes the first-difference operator; μ is the drift term; γ and δ are coefficients; ε_t is a white noise error term

3.3 ARDL Bounds Testing Approach

Given the mixed order of integration (I(0) and I(1)), we adopt the ARDL bounds testing approach proposed by Pesaran et al. (2001). The generic ARDL model is:

$$\Delta \mathrm{GINI}_t = \beta_0 + \sum_{i=1}^{p} \beta_1^i \Delta \mathrm{GINI}_{t-i} + \sum_{j=0}^{q_1} \beta_2^j \Delta \mathrm{TECH}_{t-j} + \sum_{k=0}^{q_2} \beta_3^k \Delta \mathrm{EDU}_{t-k} + \sum_{l=0}^{q_3} \beta_4^l \Delta \mathrm{GRW}_{t-l} + \phi_1 \mathrm{GINI}_{t-1} + \phi_2 \mathrm{TECH}_{t-1} + \phi_3 \mathrm{EDU}_{t-1} + \phi_4 \mathrm{GRW}_{t-1} + u_t$$

The F-statistic from the bounds test is used to test the null hypothesis of no cointegration.

Error Correction Model (ECM)
If cointegration exists, the short-run dynamics are estimated using the ECM:

$$\Delta GINI_t = \gamma_0 + \sum_{i=1}^{p} \gamma_1^i \Delta GINI_{t-i} + \sum_{j=0}^{q_1} \gamma_2^j \Delta TECH_{t-j} + \sum_{k=0}^{q_2} \gamma_3^k \Delta EDU_{t-k} + \sum_{l=0}^{q_3} \gamma_4^l \Delta GRW_{t-l} + \lambda ECM_{t-1} + \eta_t$$

Where: ECM_{t-1} is the Error correction term and λ is the Speed of adjustment parameter (expected to be negative and significant)

Lag Length Selection
In order to determine the right lag length of the ARDL model, this paper uses the Akaike Information Criterion (AIC). AIC This model-selection method is a popular methodology that is used to obtain a trade-off between good-of-fit and model-simplicity by adding a penalty on the number of parameters. This will make sure that the data is well covered by the chosen model that will not get complicated. The AIC may be formulated as follows mathematically.
$AIC = -2 \ln(L) + 2k$
and L is the value of the likelihood function, and k is the number of the estimated parameters. Above but below the AIC value, this means that the model is good as it represents both goodness of fit and parsimony (Akaike, 1974; Lutzekpohl, 2005). AIC is better used in time-series purposes due to its sensitivity to the sample size and its ability to select dynamically changing models.

Diagnostic tests
The ARDL model was estimated and some diagnostic checks were conducted to ensure the reliability of the results. Autocorrelation of the residues was studied with the assistance of the Breusch Godfrey LM test, which assists in examining whether the residuals are independent across the time (Breusch, 1978; Godfrey, 1978). The Breusch Pagan Godfrey test was used to test whether the variables have a constant variance, as it is usually used to test heteroskedasticity in regression models (Breusch and Pagan, 1979).
The test of the normality of the residual distribution was determined by the Jarque-Bera test which tests whether the remaining portion is in the normal shape which is a significant test that needs effective statistical inference (Jarque and Bera, 1987). Besides, stability of the parameters were checked using CUSUM and CUSUM of Squares (CUSUMSQ) tests. These tests are useful in establishing whether the estimated coefficients are similar over the sample period and the presence of structural instability (Brown, 1975, Durbin, and Evans). Such post-estimation checks will also make sure that the model meets the required econometric assumptions and the estimated relationships can be used to make reliable observations and policy analysis (Pesaran, Shin, and Smith, 2001; Gujarati and Porter, 2009).

Toda-Yamamoto Causality Framework
In order to supplement the analysis of the ARDL bounds-testing and Error Correction Model (ECM), we use the Toda-Yamamoto (TY) Granger causality test, to investigate the directionality of causality between technological progress and income inequality. Such a method is very useful in small-sample contexts and does not have the pre-testing biases in the traditional Granger causality tests.
The Toda-Yamamoto procedure, proposed by Toda and Yamamoto (1995), is designed to test causality without requiring cointegration or unit root corrections beforehand. It operates by estimating an augmented Vector Autoregressive (VAR) model at levels and adding extra lags corresponding to the maximum integration order of the variables in the system.
Let the maximum order of integration among the variables be denoted by dmax Suppose the optimal lag length for the VAR model is p. Then, a VAR(p + d_{max}) model is estimated, and standard Wald tests are applied only on the first ppp lags to determine causality.

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{j=p+1}^{p+d_{max}} \gamma_j Y_{t-j} + \varepsilon_t$$

Where Yt is a vector of endogenous variables: GINIt, TECHt, EDUt, GRW ; "P" is the optimal lag length from the unrestricted VAR; dmax is the maximum integration order among all variables (I(1) here), εt is the white-noise disturbance term. The Toda-Yamamoto causality test allows us to identify, for instance, whether technological innovation Granger-causes inequality, or vice versa. A unidirectional causality from TECHt→GINIt would validate concerns that technological advancement drives inequality. On the other hand, a reverse causality could indicate that rising inequality incentivizes more innovation (possibly among elites or private actors). This insight provides an essential empirical foundation for crafting targeted policies whether to regulate technology diffusion or focus on redistribution mechanisms.

4. EMPIRICAL RESULTS
This section outlines the major empirical results of the econometric investigation. The aim of the study is to determine the role played by technological advancement, education, and economic growth in shaping income inequality in India in the years between 2004 and 2024. Moreover, a structural

dummy variable (DUM2020) was added to include the initial effects of the COVID-19 pandemic, which is a large economic shock that can have changed inequality trends. The inclusion of this variable allows the analysis to capture structural changes caused by a strong economic upheaval. The empirical framework corresponds to the overall objective of the research that is to clarify the dynamics of inequality in the economy that undergoes a rapid technological and institutional change.

Pre-estimation diagnostics

It is necessary to analyze the stationarity properties of the variables before estimating the ARDL model. The concept of stationarity is that the statistical characteristics of a time series, including its mean and variance, do not change with time. The stationarity test reduces the chances of false regression outcomes that can be caused by non-stationarity data (Gujarati and Porter, 2009; Enders, 2015). To determine the rank of integration of the individual variables, typical unit-root tests like the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test are used. The tests are useful to state whether the variables are stationary at the level (I(0)) or become stationary after first differencing (I(1)) a requirement needed to use the ARDL bounds based testing approach (Pesaran, Shin, and Smith, 2001).

The time-series properties of each variable were tested before estimating the ARDL model. Three unit-root tests were used: the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) test and the KPSS test. ADF and PP tests ensure that non-stationarity is not present, and the stationarity is checked by the KPSS test. Using all three tests results in a more accurate evaluation of the order of integration.

Table 1. Unit Root Test Results (2004–2024)

Variable	ADF Statistic	PP Statistic	KPSS Statistic	Stationarity
GINI	-3.57***	-3.62***	0.42	I(0)
TECH	-1.01	-1.13	1.22***	I(1)
EDU	-2.01	-2.11	0.98***	I(1)
GRW	-3.66***	-3.70***	0.39	I(0)

Note: Author's own calculation

The outcomes provided in Table 1 show that the variables GINI and GRW are level-stationary, but the variables TECH and EDU achieve the stationarity after an initial difference. Since the combination of I(0) and I(1) orders of integration are present in the series, the Autoregressive Distributed Lag (ARDL) bounds-testing approach is considered appropriate. This is preferred when handling small samples as well as mixed integration structures and is valid even in situations when the constituent variables do not have the same order of integration. This diagnostic measure acts to protect the empirical model against spurious regressions and met the conditions self-governing to ARDL estimation.

Behaviour of the Time series

The time series behaviour and interpretation are exploring how time series behave and are interpreted in a way that completes the meaning of the concepts. The time series behaviour and interpretation are investigating the behaviour and interpretation of time series in a manner which completes the meaning of the concepts. An initial analysis of the time-series behaviour of the four variables can be used to gain helpful views of the general direction of the variables over the 2004-2024 period. The graphical analysis of every variable is provided in Appendix figure I, and the main characteristics noteable trends are depicted below hence to be interpreted. The GINI coefficient shows relatively small variations at the beginning of the period of sample, then a slow increase in the period after 2016, and a significantly steeper growth afterward in the post-2020 age brackets. This observed tendency at the empirical level implies that structural economic changes, along with the effect of the COVID 19 pandemic, might have increased the inequality in the distribution of incomes.

n the other hand, technology (TECH) variable shows the consistent positive trend over the period of observation, which confirms the gradual increase in the rate of research and development that India invests in and shows the growing relevance of the digital and technological processes in the domestic market economy.

The education variable (EDU) also documents a steady and uninterrupted rise with time and it indicates the slow gain on educational attainment and the mushrooming of human capital. However, despite this development, the disparity in the educational access and quality in different regions holds importance as an issue.

Economic growth (GRW), in its turn, has a cyclical trend, with its times of growth alternating with conspicuous slow-downs during the significant economic upheaval, especially the Global Financial Crisis and the COVID-19 pandemic.

Selection of lags and model specification

Before estimation of the ARDL model, proper selection of a lag length is critical in a bid to capture the dynamic relationship of the variables properly.

The best lag structure was read via the use of common model-selection methods such as using Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan-Quinn Criterion(HQC). As the results given in Table 2 show, the three criteria should always record that the best lag length to use in the model specification is two. This finding means that the process of adjusting the variables does not happen at once but over several periods. The choice of two lags is also supported by the existing empirical studies on emerging and developing economies, in which economic and structural adjustments generally tend to improve with time as a result of institutional constraints and lower transmission speed (Lutzkepohl, 2005; Enders, 2014).

In this regard, the official model uses an ARDL(2, 2, 2, 2) form of the equation, which provides the researcher with adequate attributes of persuading both, the short-lived proprieties and the long-lasting equilibrium association between income inequality, technological advancement, and education, and economic growth.

Table 2. Lag Length Selection Criteria

Lag	AIC	SIC	HQC
1	–4.245	–3.901	–4.129
2	**–4.502**	**–4.012**	**–4.315**
3	–4.497	–3.861	–4.240

Note: Bold indicates minimum value and Author's own calculation.

Given the confirmed lag choice, the next step is to examine whether a valid long-run relationship exists among the variables.

ARDL Bounds Testing for Cointegration

Once the correct lag length is ascertained, ARDL bounds testing methodology is used to test the existence of long-term equilibrium relationship between the variables. The Table 3 shows that the calculated F -statistic of 6.42 is greater than the upper critical value of 1 otherwise known as the 1 percent level. The outcome here is a substantial piece of statistical proof of cointegration and as such means that the levels of income inequality, technological advances, education and economic growth move in the long-term. The existence of a cointegration serves that confirmation that there is a significant long run relationship between the variables although short run fluctuations may be there. This observation justifies the applicability of ARDL model in estimating both long run coefficients and dynamic adjustments during short run so that a dynamic analysis of the factors contributing to income inequality in India over the period of study is carried out effectively.

Table 3. ARDL Bounds Test Results

Test Statistic	Value
F-statistic	6.42

Critical Values (Pesaran, Shin & Smith, 2001)

Significance Level	I(0) Bound	I(1) Bound
10%	2.72	3.77
5%	3.23	4.35
1%	4.29	5.61

The cointegration confirmation shows that the core variables have an equilibrium path that is long-run. With this determined, this model goes ahead to estimate long-run coefficients explaining the direction and strength of these the relationships.

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Long-Run Coefficients

The ARDL long-run estimates indicate that there are significant structural trends within the Indian economy. The TECH coefficient has a positive value and is significant implying that the increase in inequality in the long-term is due to the rise in technological advancement. This is in line with the accumulating literature that records the uneven allocation of the technological gains in developing economies (ILO, 2023; IMF, 2024).

Education is still playing a significant balancing role. The negative correlation between EDU clearly indicates that education to higher secondary school level decreases inequality, which serves to prove the claim that human capital reverses the disproportional impact of technology (Chaudhuri & Gupta, 2021; Tilak, 2022). Inequality is impacted by economic growth in a positive influence, which means that growth in this era was not completely inclusive. This result is in line with the evidence of recent times that shows uneven gains between various strata of the population.

Lastly, the statistical significance of structural dummy DUM2020 is positive and significant indicating a significant rise in inequality in the COVID -19 period. It coincides with a variety of measurements, according to which the pandemic hit low-skilled and informal workers more disproportionately (Oxfam, 2022; CMIE, 2023).

Table 4. Estimated Long-Run Coefficients

Variable	Coefficient	Std. Error	t-Statistic	p-value	Significance
TECH	1.041	0.249	4.17	0.000	***
EDU	−1.671	0.570	−2.93	0.006	**
GRW	0.211	0.057	3.73	0.001	***
DUM2020	0.337	0.102	3.30	0.004	***
C	−1.779	0.706	−2.52	0.018	**

*Note: ***p < 0.01, *p < 0.05.

Short-Run Dynamics and Adjustment Mechanism

In the short run, there exist short-run dynamics and short-run adjustment mechanism that can be enhanced in the future by applying the principles of the endogenous theory of innovations (Hansen, 2001).<|human|>The short-run dynamics and short-run adjustment mechanism are found in the short run and the same can be improved in future when the principles of endogenous theory of innovations are applied (Hansen, 2001).

The error-correction and the ARDL model were estimated after determining the long-run relationship where the short-run dynamics was estimated. The findings are presented in Table 5. The coefficient of the error-correction term, ECM(3), is negative, and statistically significant, and it proves that the adjustments to the long-run equilibrium are made at a relatively rapid pace.

Table 5. Short-Run Error-Correction Model Results

Variable	Coefficient	Std. Error	t-Statistic	p-value	Significance
ECM(−1)	−1.257	0.517	−2.43	0.022	**
ΔTECH	1.000	0.407	2.46	0.020	**
ΔEDU	−0.900	0.276	−3.26	0.004	***
ΔGRW	0.140	0.066	2.11	0.045	**
ΔDUM2020	0.121	0.045	2.69	0.015	**

*Note: ***p < 0.01, *p < 0.05. and Author's Own calculation

The short run coefficients are very much a replica of the long run outcomes. Technology makes the inequality more noticeable even in the short-term, whereas education decreases it. The growth only has a weak inequality -enriching effect, which agrees with the perspective that recent growth periods in India were not highly redistributive. The short-run significance of DUM2020 shows that the shock of the pandemic caused a measurable effect on inequality in the short-run.

Diagnostic Tests and Model Stability

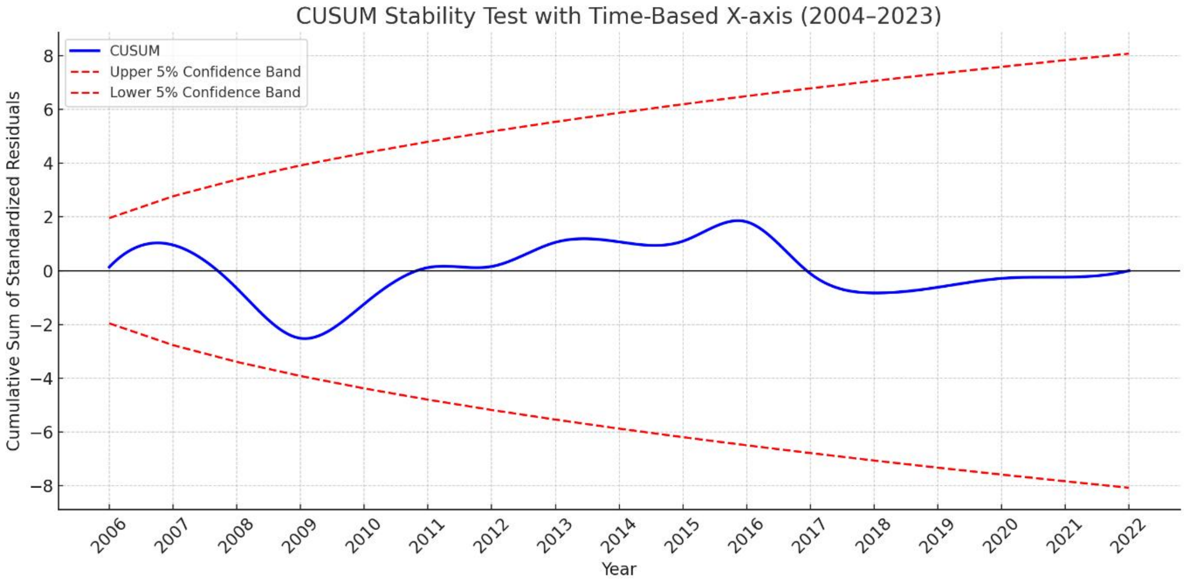
To assess the reliability of the ARDL -ECM model, a series of diagnostic tests was done. Table 6 presents the results. Serial correlation and heteroskedasticity are not found and the residual values are normally distributed. These results fulfil the key classical requirements of the regression analysis (Gujarati & Porter, 2009; Enders, 2014).

Table 6. Diagnostic and Robustness Checks

Test	Test Statistic	p-value	Interpretation
Breusch–Godfrey LM Test	1.58	0.217	No serial correlation
White Heteroskedasticity Test	1.34	0.512	No heteroskedasticity
Jarque–Bera Normality Test	0.61	0.543	Residuals normally distributed

Note : Author's Own calculation

In addition to these diagnostics, the structural stability was evaluated with the help of CUSUM and CUSUMSQ tests. Both statistics lay well within the 5% confidence bands all of the 2004-2024 including pandemic. This establishes the fact that the model parameters are stable and that expression of model estimated coefficients is appropriate in policy interpretation. It is statistically robust therefore the study proceeds to the direction of causality of the variables through Toda-Yamamoto approach.



Toda–Yamamoto Causality Analysis

To examine the causal link between the explanatory variables and income inequality, the Toda–Yamamoto non-causality test was applied. This method is advantageous for mixed-order time-series because it eliminates the need for pre-testing cointegration (Toda & Yamamoto, 1995). Table 7 presents the results.

Table 7. Toda–Yamamoto Granger Causality Test Results

Dependent Variable	Independent Variable	Chi-square Statistic	p-value	Causality
GINI	TECH	5.32	0.021	Yes
GINI	EDU	6.89	0.008	Yes
GINI	GRW	2.45	0.118	No

Note : Author's Own calculation.

The tests show one-way causality running from technology to inequality, suggesting that increases in R&D expenditure and digital penetration precede rising inequality. This finding is consistent with recent evidence on skill-biased digitalisation in developing economies (ILO, 2023; IMF, 2024).

Education also Granger-causes inequality, but its effect reduces disparities over time. This highlights the long-term importance of human capital formation in counteracting unequal technological gains (Chaudhuri & Gupta, 2021). Growth does not exhibit significant causality, reinforcing the argument that growth alone is insufficient for improving distributional outcomes without complementary policy interventions.

Having established both the dynamic and causal relationships, the final step is to derive the policy implications emerging from these results.

Policy Implications

The empirical study demonstrates how inequality in India is influenced by a set of forces of structural framework and dynamic adoptions. The steady trend is the inequality-enhancing effect of technological advancement. This highlights the issues of inclusive digital policies that can guarantee more people access to technology, affordable broadband investments and massive digital literacy programmes. This is necessary to ensure the unnecessary polarisation of the labour market through technology.

The greatest equalising factor is education. The policies to extend secondary education, to enhance the quality of the public schools, to enhance vocational and technical training can contribute to the extension of the benefits of growth and innovation. Increased focus on skill growth is of the essence to equip the workers with the ever-more automated, AI-driven, and digitalized economy.

The high effect of the pandemic dummy variable indicates that COVID-19 affected inequality in a Vivacious and sustaining manner. This requires specific fiscal assistance to workers of the informal sector, the enhancement of social protection mechanisms, and the increased investment in the health and sanitation infrastructure (World Bank, 2023). Assistance in the form of credit and digital capacity building is also important towards empowering MSMEs to reinstate fair employment provisions.

Lastly, the findings support that the economic growth in itself is not a factor to narrow the inequality. There is a need to have a more balanced model- one that fosters growth but integrates redistributive policies such as progressive taxation, rural jobs programs and affordable housing programs. These policy guidelines intertwine with India long term objectives of inclusive and sustainable development.

5. CONCLUSION

This research paper has discussed the role that technological development has played in determining income inequality in India between 2004 and 2024. The analysis was conducted through the ARDL bounds, ourselves testing approach to capture the long and short-run adjustments as well as accommodate the mixed order of integration among the variables. The Gini coefficient was used to measure income inequality and the level of technological improvement was the share of R&D spending in the GDP. As core control variables, education and real GDP per capita growth were included, a structural dummy was also used to indicate the influence of the COVID-19 shock in the post-2020 years.

The results indicate an obvious trend. The technological advancements have added to the rise of inequality in the short and long term, which is in keeping with the notion that the digitalisation and innovation favour skilled and formal workers compared to others. Education has also a somewhat counteracting effect as it diminishes inequality and assists households to adjust to the dynamic of work. The positive influence of economic growth on inequality is not very strong, and this implies that growth per se has not been inclusive enough in the process. The importance of the post-pandemic dummy also shows that the distribution pressure manifested by the COVID-19 pandemic is here to stay and it remains over low-income and informal employees.

The Toda -Yamamoto causality findings provide support of these findings by demonstrating a pre-existing causal effect of technology and education changes on inequality movements, but does not demonstrate a causal effect of economic growth. Combined with the previous findings, one can argue that there is a pattern of structural change in which India has to transform into a digital economy with the intent of ensuring that such changes are facilitated by policies that advocate equal opportunities and access to the advantages of technology.

The policy implications of the research findings include the need to implement an inclusive digitalisation policy, which should enlarge the number of people who have access to broadband, enhance digital literacy levels, and invest in re- and up-skilling. Increasing transitions Empowerment of communities through education, work opportunities and specific help on the underprivileged groups will also be key in mitigating inequalities in the long term. Meanwhile, redistributive policies like progressive taxation, urban job programmes, and more robust systems of social protection may achieve a more distributed economic growth.

LIMITATIONS AND DIRECTION OF FUTURE RESEARCH

The study is a valuable contribution of evidence, but there are a few limitations to it. Annual data limits its ability to detect short-term change at the yearly level and the restriction of the data limit the inclusion of some structural variables: informality or digital access quality. The measure of R&D might not reflect well the overall technological setting and the Gini coefficient might have both limitations in capturing all technological dimensions of inequality. Irrespective of such shortcomings, the results provide a strong base of information on the issue of the technology-inequality relationship in India.

This work can be further developed in a number of ways in the future. Different nonlinear models like Threshold ARDL or NARDL could assist in bringing out asymmetric reaction to technology shocks. A statewide panel-data study may also demonstrate differences in digital preparedness and inequality outcomes across regions in India. To further enhance the analysis the inclusion of structural pointers like labour informality, digital infrastructure indices or cover of social protection would enhance the analysis further. Newer studies will also be made to establish whether this recent increase in inequality is a permanent change or a temporary break depending on more post-pandemic data to become available.

In general, this research gives new empirical evidence on the existence of inequality-technology nexus in India. With the country still growing its digital and innovation-driven industries, the consideration of equity in the focal planning of development will be critical in ensuring that a more inclusive and sustainable future is created.

DECLARATION OF INTEREST

The authors declare that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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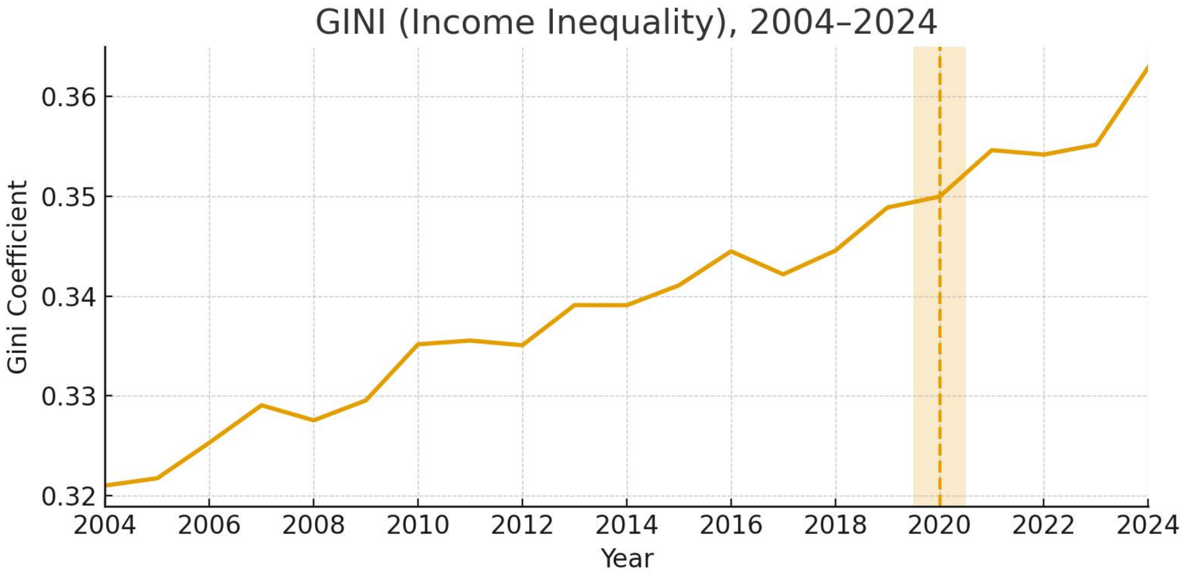
APPENDIX

Table: Variable Definitions and Sources

Variable	Notation	Definition	Source
Income Inequality	$GINI_t$	Gini coefficient of income distribution	SWIID (Solt, 2024)
Technological Advancement	$TECH_t$	R&D expenditure as % of GDP	WDI, World Bank
Education	EDU_t	Population with at least secondary education (%)	WDI, World Bank
Economic Growth	GRW_t	Annual GDP per capita growth (%)	WDI, World Bank
Period	2004-2024	Annual time series data	WDI, SWIID

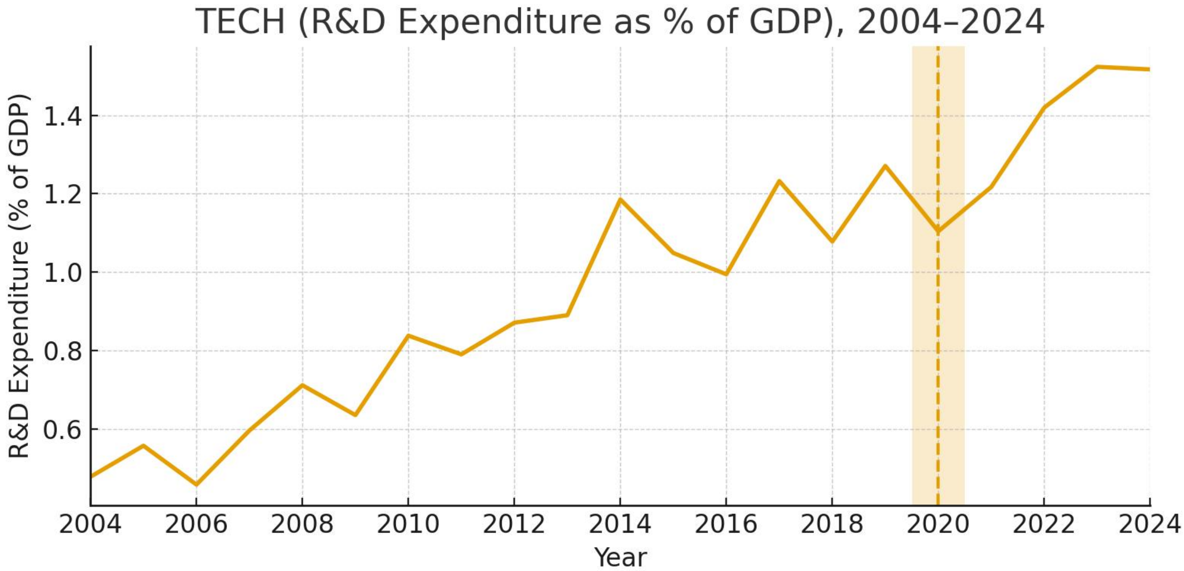
Figure A1. Time-Series Plots for Key Variables, 2004–2024

(a). GINI (Income Inequality), 2004–2024.



Note : Author's Own calculation.
The series shows moderate fluctuations in the early years, followed by a steady increase after 2016 and a sharper rise in the post-2020 phase. The shaded band marks the structural break period associated with the COVID-19 shock.

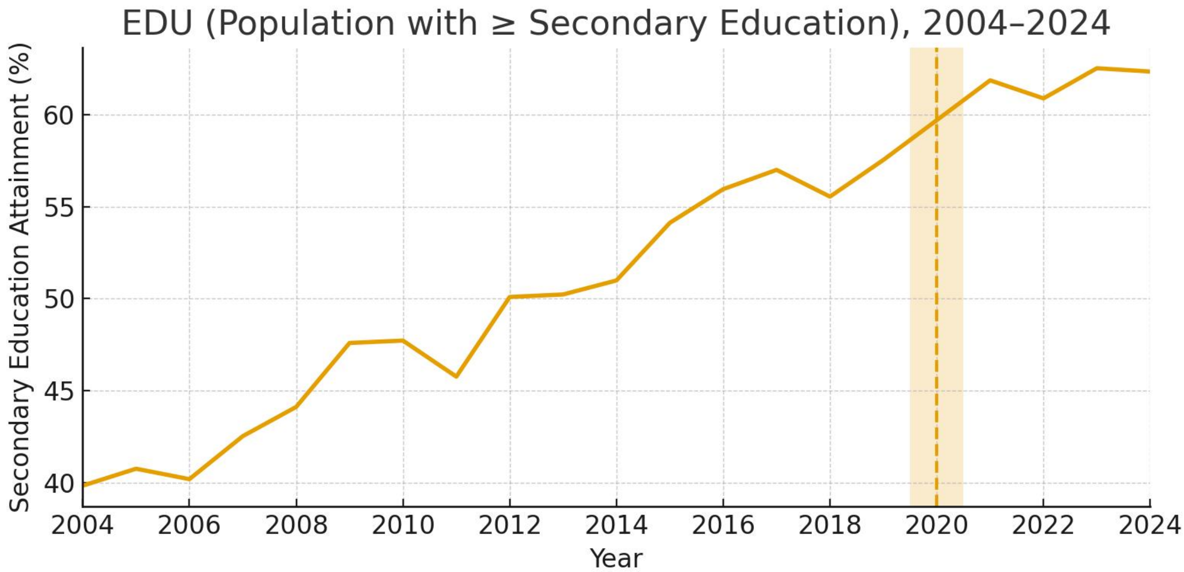
(b). TECH (R&D Expenditure as % of GDP), 2004–2024.



Note Author's Own calculation.

R&D expenditure displays a clear upward trend over the sample period, indicating gradual strengthening oIndia's innovation and technological capacity. A structural break is highlighted for 2020.

(c). EDU (Population with ≥ Secondary Education, %), 2004–2024.

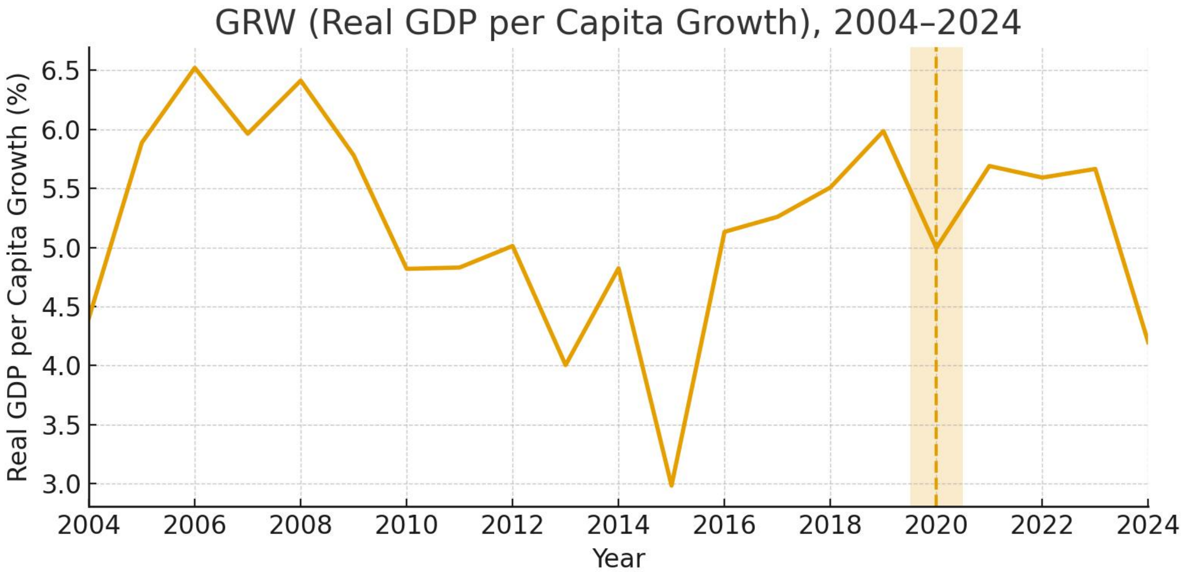


Note :

Author's Own calculation.

The education series trends upward throughout the period, reflecting improvements in secondary education attainment. The structural break in 2020 captures disruptions to schooling and human capital accumulation during the pandemic.

(d). GRW (Real GDP per Capita Growth, %), 2004–2024.



Note : Author's Own calculation.
Growth rates exhibit the expected cyclical pattern with visible downturns around major shocks, including the Global Financial Crisis and the COVID-19 period. The structural break at 2020 is marked by the shaded region.