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The Influence of Technological Innovation on Labor Productivity in Developing Asian Countries

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Abstract
This study aims to investigate the dynamic relationship between technological innovation and labor productivity in 5 Developing Asian countries (Bangladesh, India, Iran, Pakistan, Sri Lanka) from 2002-2022. Utilizing a Pool Mean Grouped/Panel Autoregressive Distributed Lag Model, it examines the extent to which technological advancements impact labor productivity in economies characterized by varying levels of development and industrialization. The results reveal that technological innovation poses a significant impact in increasing labor productivity, both in the short term and the long term. This implies that as technological innovations increase, it will bring meaningful progress in labor productivity in Developing Asian nations. Furthermore, the findings indicate that certain factors can either facilitate or impede progress toward labor productivity. In both the short and long term, technological innovation fosters sustained increases in labor productivity by enabling efficiency gains and economic growth. Inflation may temporarily disrupt productivity by distorting price signals and reducing real wages. Labor force participation and human capital investment contribute positively to productivity over time through a skilled workforce, enhancing innovation absorption and application. The presence of an error correction term in the model suggests that the dynamics of the relationship between technological innovation and labor productivity are stable over time. This implies that any deviations from the long-term equilibrium in labor productivity are corrected over time. This study provides valuable insights and recommendations for policymakers and stakeholders striving to increase labor productivity. By understanding the complex interplay between technological innovation and labor productivity, informed strategies can be developed to mitigate the adverse impacts of technological innovation on labor productivity for sustainable development.

Keywords: Technological Innovation, Labor Productivity, ARDL, Asian Countries.

Introduction

Labor productivity refers to the measurement of output generated per unit of labor input utilized in the production process. The assessment of labor, technology, and capital productivity commonly involves calculating the ratio of output to the input unit utilized in productive activities. A labor force characterized as productive and efficient has acquired the necessary training and skills, contributing to the overall enhancement of economic growth (Kahyarara, 2020).

Labor productivity examines how efficiently and effectively a firm or industry utilizes its workforce to produce goods and services. The level of labor productivity in an industry can significantly impact how competitive that industry is. Industries with high labor productivity are often better positioned to compete effectively in the market. Labor productivity does not just influence competitiveness but also directly affects the profitability of firms. When firms can produce more output with the same or fewer inputs (including labor), they tend to be more profitable. The international markets have become more competitive over time. This heightened competition makes it crucial for firms to focus on improving labor productivity to maintain or enhance their market position. Productivity is a concept that can be measured and formalized. It's about the ability of firms to achieve a specific level of output (goods and services) while using various resources, including land, labor, and capital. The labor productivity reflects the capability of firms. Firms need to develop the capability to maximize output while efficiently managing their resources. Labor is just one of several inputs mentioned; others include land and capital. Labor productivity considers how efficiently firms use all these inputs to generate output (Patra & Nayak, 2012).

Enhancing the efficiency of factors of production is of utmost significance for bolstering a nation's economic growth. Increased productivity results in reduced per-unit costs, the creation of superior-quality products, and heightened competitiveness for domestic firms in global markets, ultimately fostering export growth for the country, there are various dimensions of productivity, encompassing labor productivity, capital productivity, and total factor productivity, it is worth emphasizing the significance of labor productivity. This is because labor plays a predominant and dynamic role in the production process (Papadogonas & Voulgaris, 2005).

Nobel Laureate Paul Krugman eloquently underscores the paramount importance of labor productivity with his statement: "Productivity isn't everything, but in the long run, it is almost everything. A country's capacity to enhance its standard of living over time relies predominantly on its ability to increase output per worker." Labor productivity serves as a pivotal determinant of competitiveness, both at the national level and for individual businesses. In an era of escalating competition, labor productivity wields substantial influence, affecting the profitability of firms in both domestic and international markets. Elevated productivity not only signifies the availability of more affordable goods and services within an economy, benefiting domestic consumers, but also entices foreign investors to establish businesses within the country due to lower per-unit costs and greater profit potential. Expanding labor productivity is indispensable for elevating the quality of life and improving the well-being of workers. This is because enhanced labor productivity can result in higher wages and increased investments in human resources, ultimately contributing to a better standard of living for individuals (Heshmati & Rashidghalam, 2018).

The advancement of new technology arises from the creation of novel concepts and methods, often stemming from progress in both fundamental and practical sciences. These innovations are then adapted into practical solutions within various markets, serving to meet the demands, fulfill objectives, address challenges, or exploit significant opportunities for users. This adaptation also plays a crucial role in managing consequential problems and environmental threats (Coccia, 2019).

Innovation is not a monolithic concept; it exhibits a duality where some innovations disrupt, dismantle, and render established competencies obsolete, while others enhance and refine them. Moreover, diverse forms of innovation necessitate specific organizational settings and distinct managerial competencies. An innovation represents the initial introduction of a novel product or process into the market, characterized by a departure from established conventions in its design. Innovation and its core, the embrace of novel concepts play a crucial role in driving economic advancement. The concept of intellectual property rights encompasses various legal facets, including patents, copyrights, and trademarks, among others, each with distinct characteristics in terms of their breadth, framework, and utilization. Nevertheless, they all share a fundamental attribute: bestowing ownership rights over the economic exploitation of an idea (Fawcett & Torremans, 2001).

In many developing countries, there is a trend of consistently high birth rates. Because of this demographic pattern, it is expected that the labor force participating in various economic activities will also experience an increase. In essence, the growing population, particularly with a higher number of young individuals entering the workforce, is likely to contribute to a larger labor pool available for economic productivity. This has significant implications for the economic development and sustainability of these nations, as a larger workforce can potentially drive increased economic output and development (Maestas et al. 2023).

The firm's economics are the foundation upon which productivity is built. According to Owyong (2001), it is often quantified as the ratio of output to input. Both labour and capital productivity are examples of indicators that can be used to measure productivity. According to Lieberman and Kang (2008), the most frequent metric for assessing productivity is the labor productivity, which can be defined as the output that corresponds to the input gained from the workforce or as the value that is contributed for each hour that is worked. Productivity in the workplace is determined by three different factors. To begin, there is our human capital. In the context of the economic process, human capital is comprised of the accumulated knowledge (education and experience), talent, and expertise of an average worker. Technological advancement is the second issue to consider. The development of new products and services, which in turn leads to an increase in productivity, is typically prompted by the introduction of new inventions and innovations. According to Taylor et al. (2016), the third factor is economies of scale, which are a reduction in the costs of manufacturing. Gross outputs or added values are the standards by which capital productivity is measured. The improvement of machinery and equipment leads to an increase in capital productivity, which in turn leads to an improvement in the quality of the labour. Productivity of capital and return rate of capital are two distinct concepts that are not interchangeable. Capital productivity is a measure of both physical and partial productivity, while the other is a measure of income that relates capital income to the value of capital stock (OECD, 2001). Capital productivity is a measure of both physical and partial productivity. If one of the producers utilizes more capital, then the other producer will be exposed to different factor pricing, which will result in the two producers having fairly different levels of labor productivity. This is the case even though they both employ the same production method. Consequently, while dealing with the intensity of usage of observable factor inputs, a significant number of scholars make use of productivity as an invariability. According to Syverson (2011), this assessment is referred to as total factor productivity (TFP). It is possible to determine the total factor productivity by dividing the total output by the entire input amounts. In order to determine the total factor productivity index, the ratio of the total output index to the total input index is utilized. According to Kathuria et al. (2013), the rise in total factor productivity (TFP) necessitates that the growth rate in total output be lower than the growth rate in total input on account of this rationale.

As a result of the extensive growth driven by reform and opening up, there has been a remarkable and unprecedented surge in scientific and technological innovation. This wave of progress has significantly transformed industries, bringing both opportunities and challenges. On one hand, traditional or backward industries have experienced disruptions, with workers in these sectors increasingly losing their positions due to the rapid pace of technological change. These industries, unable to keep pace with innovation, are being displaced, creating visible employment issues as a significant portion of the workforce finds itself out of step with the demands of a more technologically advanced economy. On the other hand, the rise of new industries, fueled by technological breakthroughs, has simultaneously opened up new avenues for employment. These emerging sectors are absorbing labor and offering new opportunities, though not always at a rate sufficient to offset the losses from declining industries. This dual process highlights a growing tension within the labor market, as shifts in employment patterns expose vulnerabilities among workers who may lack the skills required for jobs in innovative sectors. However, despite these challenges, the fundamental role of technological innovation in driving social progress cannot be overlooked. Technological advancements are essential for societal development, fueling economic growth, improving living standards, and addressing global challenges. Yet, this progress must be carefully managed, particularly in its relationship with employment. Social harmony, a critical aspect of societal well-being, is closely tied to full employment. Without ample opportunities for employment, social inequalities may deepen, and unrest can emerge, threatening the fabric of social cohesion. Therefore, while innovation propels economic and social growth, it is essential that it does not come at the expense of broad-based employment opportunities. The relationship between technological innovation and employment is not only interconnected but also deeply complex, requiring careful analysis and strategic intervention to ensure that both progress and social stability are maintained. In this context, understanding the impact of technological progress on employment becomes crucial for achieving harmonious societal development (Lin et al., 2013; Zhou et al., 2005). The rapid advancements in science and technology present both opportunities and risks, making it essential to study how technological innovation influences job creation and displacement.

Moreover, it is critical to investigate how technology can be integrated with employment in a way that promotes a "benign interaction" between the two. This means fostering a relationship where technological advancements do not erode the job market but instead work in tandem with efforts to create new, sustainable employment opportunities. Achieving this requires a balanced approach, one that leverages innovation while also investing in education, reskilling, and other social policies that help workers transition into new roles. The need to explore this relationship between technological innovation and employment is not just of theoretical interest; it has immediate and practical implications for policymakers, businesses, and society as a whole. In the current era, where the power of science and technology is reshaping economies at an unprecedented rate, understanding how to manage the interaction between innovation and employment has become a pressing issue. The goal is to create a dynamic where technological progress fuels economic growth without leading to widespread unemployment or social inequality. By elucidating the mechanisms through which technological innovation and employment can organically integrate, it becomes possible to craft policies that foster inclusive growth, ensuring that technological advancements contribute to a more prosperous and harmonious society (Li, 2021).

Literature Review

Chudnovsky et al. (2006) examine the determinants of innovation and its impact on productivity in Argentine manufacturing firms using panel data from 1992–2001. The study finds that in-house R&D and technology acquisition significantly increase firms' likelihood of innovating. Innovation, in turn, boosts productivity and competitiveness, with larger firms more likely to

engage in such activities due to greater resources. The paper offers key policy implications for fostering innovation and supporting SMEs in developing economies.
Miguel (2006) examines the relationship between R&D, innovation, and firm productivity in Chile, using a structural model to correct for biases. The study finds that larger firms with greater market power are more likely to invest in R&D and innovate. However, unlike expectations, these innovations show no immediate effect on firm productivity in the short run. This suggests that in emerging markets, productivity gains from innovation may take longer to materialize or depend on complementary factors.
Crespi and Zuniga (2012) analyze how innovation affects labor productivity in six Latin American countries using firm-level data. They find that firms investing in knowledge and technological innovation achieve higher productivity. However, the drivers of innovation are diverse and fragmented across countries, with weak ties to scientific and market information sources. The study highlights the need to strengthen innovation systems to boost productivity and competitiveness in the region.
Zuniga and Crespi (2013) examine how different innovation strategies affect employment growth in four Latin American countries. They find that in-house R&D ("make only") has the strongest positive impact on employment, followed by mixed "make and buy" approaches. High-tech industries benefit most from internal innovation, while low-tech sectors gain from both internal and external sources. Product innovation is mainly driven by in-house R&D, whereas process innovation relies more on external technologies.
Álvarez et al. (2015) and Fuentes et al. (2015) examine the relationship between innovation and productivity in Chile's service sector, using manufacturing as a benchmark. Both find that while innovation drivers are broadly similar across sectors, their relative importance and mechanisms differ. In both services and manufacturing, higher innovation investment boosts labor productivity, though services face unique innovation challenges. The studies highlight the need for sector-specific innovation policies to enhance productivity and competitiveness.
Arntz et al. (2016) use a task-based approach to estimate automation risk in 21 OECD countries, finding only 9% of U.S. jobs highly vulnerable, much lower than Frey and Osborne's 47%. Acemoglu and Restrepo (2017) show industrial robots reduced U.S. employment and wages from 1990–2007, with significant local labor market effects. Autor and Salomons (2017) find rising productivity cuts jobs within industries but boosts overall employment through positive spillovers. Reijnders and de Vries (2018) reveal that technological progress increased nonroutine task shares globally, though task relocation effects diverge between developed and developing economies.
Graetz and Michaels (2018) find that robot adoption in 17 OECD countries (1993–2007) boosted labor and total factor productivity without significantly reducing total employment, though it lowered low-skill job shares. Ramírez et al. (2020) show that human capital plays a crucial, causal role in driving R&D investment, innovation, and productivity within Colombian manufacturing firms. Their study highlights that previous research underestimated human capital's importance. Walheer (2021) examines labor productivity growth through efficiency, technological change, and capital–labor ratios, finding divergence and heterogeneity across global technology clubs. Advanced economies shape global technology, while follower countries adopt similar strategies but with varying outcomes.

Research Gap

The study will investigate the effects of technological innovation on labor productivity in developing Asian countries. Although several research studies have been conducted regarding labor productivity, there has been a debate among researchers and policymakers about technological innovation. Literature highlights those countries that focus on labor productivity due to technological innovation (Cassiman & Golovko, 2011). This study will focus on the outcomes of technological innovation in certain developing Asian countries that are (Bangladesh, India, Iran, Pakistan, Sri Lanka). There is a critical lack of literature regarding technological innovation and labor productivity in developing Asian countries. This research will close this gap. This study also contains several more significant factors that significantly contribute to labor productivity (explained in the section on the description of the variables).

RESEARCH METHODOLOGY

This study uses panel data (2001–2022) from Bangladesh, India, Iran, Pakistan, and Sri Lanka to examine the impact of technological innovation on labor productivity. Variables include labor productivity, technological innovation, capital formation, globalization, and human capital investment. Panel data methods are applied for analysis.

A discussion of each of the variables that were taken into consideration throughout the analysis is presented in the next section. In addition to this, it detailed the characteristics of the variable, the thoughts that led to the selection of that particular variable, as well as the value that was anticipated to be associated with the variable. The symbols, measures, and data sources associated with the variables are shown in the description variable table 3.1, which is organized in the following manner:

Table 1: Description of variables

Indicators	**Denoted by**	**Gaged**	**Sources**
Labor productivity	*LP*	Measured as index number using the ratio of real GDP in USD to total employment in percentage.	World Bank (2024)
Technological innovation	*TI*	Patent applications, residents use as a proxy for Technological Innovation	World Bank (2024)
Capital formation (K)	*CF*	Capital formation will be measured as constant LCU	World Bank (2024)
Globalization	*GLOB*	Globalization index is used and measured in index numbers	KOF (2024)
Human-capital investment	*HCI*	Government expenditure on education in USD is taken proxy for human capital investment.	World Bank (2023)

Panel data approximations enhance estimation power by increasing observations and addressing limitations of individual time series. Unit root tests, using models like the AR(1) equation:

$$Z_{it} = \emptyset Z_{it-1} + e_{it}$$

check for stationarity to avoid false regressions. Tests like IPS and LL help detect unit roots and ensure reliable panel data analysis.

This study applies the Levin-Lin (LL) unit root test to detect non-stationarity, using a model with an intercept but no trend. The test employs the following form:

$$\Delta y_{it} = a_0 + \emptyset\, y + \sum_{i=1}^{p} \beta_i\, \Delta y + e_{it}$$

Here, a_0 is the intercept, $\emptyset$ the slope, and *e_it* the residual term, with lags from 1 to *p* as per Levin et al. (2002).

The Im-Pesaran-Shin (IPS) test, introduced by Im et al. (1997), improves on the Levin-Lin (LL) test by allowing coefficient heterogeneity across panels. It averages individual.

ADF-t-statistics-as:

$$t = \frac{1}{N} \sum_{i=1}^{N} t\, p_i$$

The general model is given by.

$$\Delta Y_{it} = \alpha_i + \sigma_i Y_{i,t-1} + \sum_{k=1}^{n} yik \; \Delta Y_{i,t-k} + \delta_i t + \emptyset_i t + u_{it} t$$

The mixed order of integration supports using the ARDL model, which handles variables stationary at I(0) and I(1). It's flexible for examining variable interactions with cross-sectional dependency. The study uses both the PMG estimator (assuming long-run homogeneity) and the MG estimator (allowing full heterogeneity). PMG is more efficient when long-run relationships are stable but short-run dynamics differ, while MG suits highly heterogeneous cases. Estimating both ensures robust findings.

The model specification is:

LP = f(TI, CF, GLOB, HCI)

Where LP = Labor Productivity, TI = Technological Innovation, CF = Capital Formation, GLOB = Globalization, and HCI = Human Capital Investment.

The ARDL model is a flexible tool for examining both short- and long-term variable relationships without pre-testing integration orders. It effectively handles variables with mixed stationarity and addresses endogeneity issues, improving the reliability of empirical results. Its adaptable lag structure captures both immediate and delayed effects. However, ARDL may struggle with variables stationary only after the second difference. Despite this, it remains widely used for its versatility in time series and panel data analysis across fields like economics and finance.

Conclusions:

Labor productivity measures output per unit of labor input and reflects how efficiently firms utilize resources in production (Kahyarara, 2020). High labor productivity enhances firm competitiveness and profitability, especially in increasingly competitive international markets. This study examines the impact of technological innovation on labor productivity in five developing Asian countries (Bangladesh, India, Iran, Pakistan, Sri Lanka) using panel data from 2001–2022. Variables include Labor Productivity (dependent) and Technological Innovation, Capital Formation, Globalization, and Human Capital Investment (independent). Panel unit root tests (LLC, IPS) confirmed mixed stationarity levels, leading to panel cointegration analysis. The ARDL model explored both long- and short-run relationships. Results show positive, significant effects of technological innovation, globalization, capital formation, and human capital on labor productivity. The error correction term confirms dynamic model stability.

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