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# Understanding Skill-Biased Technological Change in India: A Sectoral Analysis

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**ABSTRACT**
Skill-Biased Technological Change(SBTC) refers to a shift in production practices that increases the value of skilled worker relative to unskilled worker by increasing its productivity and, consequently, its demand. SBTC reshapes India's workforce by boosting demand for trained labour, particularly in tech-driven industries, while diminishing chances for low-skilled workers. As a result, conventional businesses like manufacturing and agriculture are disrupted, pay differences grow, and inequality increases. Using sector-wise and aggregate data from the Employment and Unemployment Survey(EUS) and Periodic Labour Force Survey(PLFS) for the period 1993-94, 2004-05, 2011-12, 2018-19 and 2022-23, we investigate whether skill-biased technological change was responsible for the rise in skilled labour in India. At the industry level, we calculate the rate of skill-biased technological development. In each industry, we create metrics for the proportion of skilled to unskilled employment and skilled to unskilled salaries. This data produces estimates of structural parameters based on a link suggested by representative firms' profit-maximizing conduct. We discover that skill-biased technology development has occurred in the majority of industries, the rate of change has differed greatly throughout.

**Keywords:** Skill-Biased Technological Change; Skilled Workers; Unskilled Workers; Profit Maximizing

**JEL Codes:** C21; J24; J31; L16; N35; O15; O33

## Introduction

Technological developments that disproportionately boost demand for skilled labour—typically benefiting people with technical competence and higher education—while decreasing demand for unskilled labour are referred to as Skill-Biased Technological Change, or SBTC. One idea says that as the number of skilled workers goes up, the pay bonus goes down because of the short-term substitution effect. Acemoglu (1998) says that the endogenous technical change(SBTC) moves the demand curve to the right and raises the wage premium. Increased pay gaps and changes in employment trends are frequent outcomes of this phenomena (Acemoglu, 1998). By facilitating automation, digitisation, and AI-driven processes that prioritise technical and cognitive abilities, SBTC has revolutionised businesses worldwide (Autor et al., 2003).

With more than 500 million workers across a wide range of industries and skill levels, India is a crucial case study for SBTC (World Bank, 2019). India is one of the fastest-growing economies, and its industries—which include labour-intensive agriculture, technology-driven IT, and manufacturing—offer a distinctive setting for analysing the various effects of SBTC (NASSCOM, 2021). Rapid urbanisation and digital transformation in the nation underscore how differently different businesses and areas have adapted to technological change. For instance, SBTC greatly benefits financial and IT services, but it has a negative impact on traditional industry and agriculture, which exacerbates inequality (McKinsey, 2020).

We investigate whether skill-biased technological change was responsible for the rise in skilled labour in India, using sector-wise and aggregate data from the National Sample Survey Office (NSSO) Employment and Unemployment Survey (EUS) and Periodic Labour Force Survey (PLFS) for the years 1993–1994, 2004-05, 2011-12, 2018-19 and 2022–2023. We compute the rate of SBTC at the industry level. Based on survey data, workers are categorised into 11 industrial categories, and their level of education determines whether they are considered skilled or unskilled. We provide measures for the ratio of skilled to unskilled jobs and skilled to unskilled wages in each industry. Based on a connection implied by the profit-maximizing behaviour of representative firms, the data generate estimations of structural parameters of interest. We find that most industries have seen SBTC, the pace of change has differed greatly throughout.

## Literature Review

Studies on SBTC conducted worldwide look at how technology developments reduce the need for low-skilled labour while disproportionately favouring skilled labour. The fundamental idea put out by Acemoglu (1998) is that technology advancements tend to replace unskilled labour and enhance skilled workers, which increases pay disparity. Autor, Levy, and Murnane (2003) expand on this concept by highlighting how automation and computerisation have increased the need for people with sophisticated technical abilities, particularly in industrialised nations.

Research from OECD countries demonstrates that SBTC has contributed to the growth of high-tech manufacturing, IT, and financial sectors, which pay highly trained people (Berman et al., 1994). On the other hand, traditional industries like low-skilled manufacturing and agriculture have shrunk or stalled, which has exacerbated pay disparity and employment polarisation (Goos & Manning, 2007). Doms, Dunne, and Troske (1997) also draw attention to how technological innovation contributes to skill gaps, noting that even within industries, companies that use cutting-edge technology typically provide better working conditions and higher wages than those that don't.

Although SBTC has increased productivity and stimulated economic growth in certain areas, it has also caused serious problems for labour markets, particularly with regard to inequality. For instance, Goldin and Katz (2008) contend that technology advancements that benefitted highly educated workers caused the pay gap to increase in the United States, whereas lower-skilled individuals faced job losses or stagnant salaries.

All things considered, research from throughout the world shows that SBTC has been a major contributor to economic polarisation, with technology developments creating a higher need for skilled workers in some industries while reducing chances for unskilled workers (Katz & Autor, 1999).

Although there is considerable study on the effects of SBTC in India, there are still a lot of unanswered questions. There is little sector-specific analysis in the majority of the current work, which mostly concentrates on general economic patterns. Although Chamarbagwala (2006) investigated the connection between economic liberalisation and pay inequality, he did not particularly look at how technology affects this disparity across industries. Furthermore, the consequences of SBTC in rural or agricultural contexts are still little understood, with the majority of the study concentrating on urban industries like IT and services. Hota & Verma (2022) note that India's adoption of automation in agriculture is still in its infancy compared to manufacturing or services, making it an under-researched area for SBTC.

Additionally, SBTC's spatial dimension—which draws attention to regional differences in the adoption of technology—is still ignored. Although McKinsey (2020) and NASSCOM (2021) offer valuable perspectives on urban India, further focus is still required to address the disparity in skill acquisition and technology advancement between rural and urban areas. The examination of informal labour markets, where the effects of SBTC are less well-studied, particularly in traditional sectors and small businesses, is a significant gap.

There have been noticeable differences in technology adaption among Indian sectors. The need for qualified experts in programming, data science, and artificial intelligence has increased significantly as a result of SBTC's substantial expansion in the IT and software services industries. According to NASSCOM (2021), India's robust tech skill base has made it a global centre for IT outsourcing. The growth of e-commerce and financial technology (FinTech), two industries that significantly depend on skilled labour and have profited from SBTC, is also highlighted by McKinsey (2020). However, the effects have been more uneven in the industrial sector. While certain industries, like electronics and autos, have become more automated, others—especially small and medium-sized businesses (SMEs)—are falling behind in implementing cutting-edge technology.

Chamarbagwala (2006) states that the industrial sector's inability to adapt to new technology is hampered by issues like obsolete infrastructure and a shortage of trained workers. Furthermore, SBTC implementation has been sluggish in India's agriculture sector, which employs a sizable share of the country's workforce. Precision farming and other technological innovations have gained considerable traction, but Hota & Verma (2022) note that these developments are still scarce and concentrated in specific areas, with large swaths of rural India still using conventional techniques.

In conclusion, although studies conducted worldwide have shown that SBTC has a wide range of consequences, India's sectoral reactions to technological advancements are still unequal, with a dearth of study on the rural and informal sectors. To lessen inequality and guarantee sustainable growth, further research is required to determine how various industries and geographical areas may more effectively adjust to SBTC.

## Data and Methodology

### Data

The sources of the statistics for workers and wages are the unit level data from EUS for 1993–1994, 2004-05 and 2011–12 and PLFS for 2018–19 and 2022–23. In every survey wave, these surveys seek to provide comprehensive socioeconomic data. The survey's goal is to collect data on the work situation of every household member, including age,

educational background, industry of employment, pay, and other variables. The survey records the employees' principal and subsidiary job statuses.
In the United States, workers with a high school diploma are unskilled, but those with a college degree are skilled, according to Acemoglu (2002). However, most worldwide surveys show that talented workers possess at least a high school degree. Furthermore, those between the ages of 15 and 64 who have finished at least a higher secondary school education are considered skilled workers in India, according to a study by Unni and Rani (2004). Furthermore, the remaining people in the age group are thought to be unskilled. As a result, we select workers from the survey data who are between the ages of 15 and 64. We categorise those with upper secondary education and above as skilled, including those who have completed skill-enhancing courses and remaining workers are categorised as unskilled. Agriculture, Forestry, and Fishing; Mining and Quarrying; Manufacturing; Electricity, Gas, and Water; Construction; Trade; Hotel and Restaurant; Transport, Storage, and Communication; Finance, Real Estate and Business; Services, and Total are the industry groups that are established by industry concordance between NIC-1987, 1998, 2004, and 2008.

Finally, because the EUS and PLFS employ distinct methodologies, comparisons are problematic. Moreover, these surveys tend to understate the population when compared to census data. We thus estimate the ratios of skilled to unskilled labourers and the accompanying salary ratios in order to resolve these problems.

**Methodology**
There are various Constant Elasticity of Substitution(CES) production functions in this literature which can be used to study the relation between wage ratio and skilled-unskilled workers ratio and detect presence of SBTC. These are as follows:
First,

$$Y = [\gamma_L (A_L L)^{\frac{e-1}{e}} + \gamma_H (A_H H)^{\frac{e-1}{e}}]^{\frac{e}{e-1}} \qquad (1)$$

where Y is the output, L & H are low- and high-skilled workers respectively, e is elasticity of substitution between skilled and unskilled workers, $A_L$ & $A_H$ are unskilled and skilled worker-augmenting technology respectively, $\gamma_L$ & $\gamma_H$ are importance of the two factors and $\gamma_L + \gamma_H = 1$.
Second,

$$Y = K^{\alpha}[\left\{\gamma_L (A_L L)^{\frac{e-1}{e}} + \gamma_H (A_H H)^{\frac{e-1}{e}}\right\}^{\frac{e}{e-1}}]^{1-\alpha} \qquad (2)$$

where $\alpha \in (0, 1)$ is the relative importance of capital (K). This is a nested CES function which takes into consideration other factors of production, like capital.
Since the major coefficient of interest is the elasticity of substitution, which is the same from any of the aforementioned functions and maintaining the minimal assumptions necessary as a CES production function for estimating elasticity, Daron Acemoglu, in a lecture at MIT, provided the canonical model in this literature:

$$Y = [(A_L L)^{\frac{e-1}{e}} + (A_H H)^{\frac{e-1}{e}}]^{\frac{e}{e-1}} \qquad (3)$$

We opt for production function (3) for estimating the parameters of interest.
The following procedures are usually used by researchers, regardless of the above mentioned CES production functions. First, by obtaining derivatives of Y with respect to L and H, marginal products are produced. The equality of the wage ratio and the ratio of marginal products is implied by the presumption of competitive labour markets. The resulting skill premium is defined by equation 6 below:

$$W_H = \frac{\partial Y}{\partial H} = A_H^{\frac{e-1}{e}}[A_L^{\frac{e-1}{e}}(H/L)^{-\frac{e-1}{e}} + A_H^{\frac{e-1}{e}}]^{\frac{1}{e-1}} \qquad (4)$$

$$W_L = \frac{\partial Y}{\partial L} = A_L^{\frac{e-1}{e}}[A_L^{\frac{e-1}{e}} + A_H^{\frac{e-1}{e}}(H/L)^{\frac{e-1}{e}}]^{\frac{1}{e-1}} \qquad (5)$$

$$\omega = \frac{W_H}{W_L} = (\frac{A_H}{A_L})^{\frac{e-1}{e}}(\frac{H}{L})^{\frac{-1}{e}} \qquad (6)$$

or

$$ln\omega = \frac{e-1}{e}\, ln\left(\frac{A_H}{A_L}\right) - \frac{1}{e}\ln\left(\frac{H}{L}\right) \qquad (7)$$

where $W_H$ and $W_L$ denote the wages of skilled and unskilled workers respectively and ω is the skill premium. It demonstrates that the relative demand curve for skill is downward sloping for the given technological advancement. It goes without saying that when skilled workers are harder to find, the skill premium rises:

$$\frac{\partial ln\omega}{\partial \ln\left(\frac{H}{L}\right)} = \frac{-1}{e} < 0 \qquad (8)$$

This is the typical substitution effect. The magnitude of the effect of $H/L$ on the skill premium decreases with increasing substitution elasticity (e). It is helpful to understand how the talent premium reacts to technology given the subject of this article. It is important to note that the skill premium's ability to adapt to technological advancements depends on the elasticity of substitution:

$$\frac{\partial ln\omega}{\partial \ln\left(\frac{A_H}{A_L}\right)} = \frac{e-1}{e} \qquad (9)$$

In case of $e > 1$, when skilled people become relatively more productive or when technology supports skilled labour, that is when $A_H/A_L$ increases, the skill premium rises. From Tinbergen(1974), it can be concluded that "technological development" must have raised the demand for skills in order to keep the relative earnings of skilled people from falling(Acemoglu & Autor, 2010). This rise in demand for skills(D) is given by:

$$D = (\frac{A_H}{A_L})^{\frac{e-1}{e}} \quad (10)$$

where $A_H/A_L$ is the skill supporting technical change and is given by:

$$\frac{A_H}{A_L} = T = \frac{(\frac{W_H H}{W_L L})^{\frac{e}{e-1}}}{\frac{H}{L}} \quad (11)$$

**Results and Discussion**

From equations 8, 9 and 10, it is clear that elasticity of substitution between skilled and unskilled workers is an important factor to study the effect of rise in H/L and technology change on wage premium. According to Acemoglu (2002), it is difficult to determine the elasticity. It has been the subject of several research in developed countries, with a wide range of final estimates. The authors of the consensus figure that falls between 1 and 2 are Ciccone and Peri (2005), Goldin and Katz (2008), Katz and Murphy (1992), and Autor et al. (2008). As of yet, no decision has been made, with an emphasis on developing nations. We found two papers: one by Psacharopoulos and Hinchliffe (1972) that estimates values between 2.1 and 2.5, and another by Tinbergen (1974) that suggests values between 0.4 and 2. Behar (2023) and Manacorda et al. (2010) suggested values between 2 and 4. The numbers stated in the cited literature are consistent with the estimate of the elasticity, e = 1.5, in our previous study.

Between 1993–94 and 2022-23, $A_H/A_L$=T for the aggregate economy increased from 0.02 to 1.70, and the resulting demand for skills(D) increased from 0.28 to 1.19(Table 1). This responds to our query that the expansion of the skill-based workforce during the study period in our previous study is caused by skill-biased technical transformation for the aggregate economy.

**Table 1 :Technical change($A_H/A_L$=T) and Demand Index (D)**

| Industry groups | T | | D | |
|---|---|---|---|---|
| | 1993-94 | 2022-23 | 1993-94 | 2022-23 |
| Agriculture, Forestry and Fishing | 0.00 | 0.00 | 0.02 | 0.22 |
| Mining and Quarrying | 0.14 | 1.29 | 0.33 | 1.16 |
| Manufacturing | 0.01 | 0.49 | 0.29 | 0.83 |
| Electricity, Gas and Water | 0.59 | 0.25 | 0.29 | 1.33 |
| Construction | 2.97 | 2.14 | - | - |
| Trade | 2.52 | 1.57 | 3.51 | 1.85 |
| Hotel and Restaurant | 5.30 | 2.26 | 0.01 | 0.13 |
| Transport, Storage and Communication | 2.02 | 2.10 | 3.05 | 3.26 |
| Finance, Real Estate and Business | 80.9 | 99.2 | 1.59 | 1.95 |
| Services | 2.30 | 2.30 | 2.40 | 2.40 |
| Total | 0.02 | 1.70 | 0.28 | 1.19 |

Note: Authors' calculations.

Agriculture, Forestry, and Fishing, showing constant growth, this historically labour-intensive industry has seen little technical breakthroughs. The demand for skills increased showing increasing need for skilled labour. Agriculture is heavily relied upon. It has evolved into a lifestyle. There are no contemporary activities seen here save from a few exceptional instances of innovation. Mining and Quarrying has a consistent increase in T, indicating a slow uptake of skill-based technologies. Also a notable increase in D, indicating a surge in the need for qualified experts in resource extraction. Manufacturing, reflects increased production processes and automation with increasing technical change ratio. Increased skill needs as a result of technology integration are also demonstrated with the demand index values. There has been a terminal collapse in all of the old manufacturing hubs, including Kanpur, Kolkata, Ludhiana, Panipat, etc. Additionally, MSMEs have resisted expansion and appear to be lacking in vitality. Electricity, Gas and Water, significant changes driven by technology are reflected in the changes in T. However, a consistent increase in D is highlighting the need for skilled workers in utilities and the energy sector. Construction, limited use of technology is shown in the fall in T. Here D is not be calculated due to very low elasticity of substitution value. Primitive technology is used in the construction industry. Transport, Storage and Communication shows an increase in technical change. And an increase in

D indicates a persistently strong need for qualified workers in communication and logistics. Same goes with Finance, Real Estate and Business. The performance of T and D in Services is constant.

The widespread influence of SBTC is shown in the evident trend of rising skill demand across many of the above industries. Industries with more access to capital and infrastructure tend to have a concentration of skill-biased technology adoption (Acemoglu, 2003). Wage gaps between skilled and unskilled workers result from technical improvements which raise the need for skilled labour by emphasising on automation and digitalisation (Goldin and Katz, 2008). The study by Autor (2015), which claims that automation reshapes industries, generating high-skill possibilities while shrinking low-skill employment, is consistent with the general growth in 'T' and 'D' in the majority of sectors, indicating skill-biased shifts.

**Conclusion**

The study's conclusion emphasises the widespread effects of Skill-Biased Technological Change(SBTC) on Indian sectors, pointing out important patterns and differences. In most industries, SBTC has raised the need for skilled people, which is consistent with the general finding that productivity gains from new technologies favour skilled labour (Acemoglu, 1998; Autor, Levy, & Murnane, 2003). This is seen in industries that use data-driven innovations and sophisticated digital technologies. Because they have less access to capital and infrastructure, sectors like construction and agriculture implement SBTC more slowly. This finding is consistent with studies by Chamarbagwala (2006) and Hota & Verma (2022), which highlight the resource and structural barriers that traditional sectors must overcome in order to adopt technology. In line with research by Goldin and Katz (2008) and Katz and Murphy (1992), the unequal expansion of SBTC widens the pay gap between skilled and unskilled labour. While low-skilled workers confront stagnating or declining earnings, high-skilled sectors attract considerable wage premiums.

**Policy Suggestions**

The World Bank's (2019) and Autor (2015) suggestions are in line with investments in education and training programs to improve technical capabilities, especially in lagging sectors.
According to the International Labour Organisation, equitable technology access is the promotion of inclusive access to digital infrastructure and technology in order to lessen sectoral and regional imbalances.
Speaking at the Global Economic Policy Forum 2024, World Bank Chief Economist Indermit Gill said, "Despite the increasing demand for skilled labour, India continues to underutilise a major portion of its talent pool, particularly women." Although SBTC has spurred innovation and economic growth in high-tech industries, its unequal implementation presents obstacles to labour market inclusion. For economic development to be equitable and sustainable, these gaps must be addressed by specific policies.

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