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Gross Value-Added Growth, Real Wages, Structural Transformation, and Employment Dynamics in India: Linear and Nonlinear Evidence from ARDL and NARDL Analysis (1981–2022)

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Abstract

India's post-reform economic trajectory has been characterized by sustained growth in Gross Value Added (GVA), driven predominantly by rapid productivity gains and output expansion in the service sector. While this growth has contributed significantly to poverty reduction and improvements in living standards, it has not translated proportionately into employment generation, resulting in persistent concerns over jobless growth. This paradox is particularly salient in the context of India's evolving demographic structure, rising labour force participation, and accelerating technological change.

This study examines the dynamic linkages between GVA growth, real wages, structural transformation, and job creation in India over the period 1981–2022. Using the India KLEMS (2024) database, the analysis adopts an Aggregate Production Possibility Frontier (APPF) framework to decompose GVA growth by factor inputs and sectoral contributions. To empirically investigate the employment–growth–wage nexus, both linear Autoregressive Distributed Lag (ARDL) and nonlinear ARDL (NARDL) models are employed, allowing for asymmetric responses of employment to positive and negative changes in economic growth and wages.

The results reveal three key findings. First, economic growth exerts a positive and statistically significant effect on employment creation in the long run, though the magnitude of this effect varies across sub-periods marked by structural breaks. Second, real wage growth is found to exert a dampening effect on employment, reflecting cost pressures in a labour market characterized by informality and uneven productivity gains. Third, and most importantly, the nonlinear estimations indicate strong asymmetries: negative shocks to GVA growth and real wages have a considerably larger adverse impact on employment than the positive effects generated by equivalent increases. This highlights the vulnerability of India's labour market to downturns and underscores the limited employment-absorbing capacity of its growth model.

The findings suggest that India's services-led growth and capital-intensive structural transformation have weakened the traditional employment elasticity of growth. Policy implications point toward the need for a rebalanced development strategy that strengthens manufacturing and labour-intensive services, promotes wage-productivity alignment, and enhances the resilience of employment to macroeconomic shocks.

Keywords

Gross Value Added (GVA); Real Wages; Employment Generation; Structural Change; ARDL Model; NARDL Model; India; Labour Market Dynamics

1. Introduction.

Many articles have discussed the outstanding performance of Indian economic growth in recent decades, many of which have compared its performance with that of its giant neighbor (China) in many areas such as rapid growth, poverty reduction, high rates of income inequality, etc. However, the unique feature of the Indian economy's performance as a service economy par excellence has made it face a significant challenge in its performance and ability to create sufficient job opportunities to meet the growth in supply to the domestic labor market. Fortunately, demographic changes in the population structure are mitigating this challenge, with a decline in population growth of approximately -0.05 percentage points on average between 1991 and 2022 according to World Bank data, but this has been accompanied by an increase in the participation rate of the working age group (15-64) from 58.1% in 1991 to 67.7% in 2022. This has kept unemployment rates at an average of 7.7% per year over the same period according to World Bank data.

There are many factors that determine the amount of jobs in any society, and these factors are multiple, interrelated taking its features by way of economic, social and political, technological and demographic aspects. Refocusing on the importance of creating jobs is even more pertinent in today's day and age. Automation, according to a study by the McKinsey Global Institute, could eliminate as many as 800 million jobs worldwide in 2030, with up to 375 million workers needing to learn new skills (McKinsey Global Institute, 2017). Adoption of some of these advanced technologies will be adopted at a much faster rate than average employers globally in India with 35% believing that semiconductors and computing technologies, followed by quantum and encryption technology (21%) stand to be the most transformative for their business (World Economic Forum, 2025). India is expected to have to generate 143 – 324 million jobs by 2050 to absorb the growth in population (Alonso & MacDonald, 2024).

This central claim is the following: A reduction in job creation leads to more unemployment and an increase in individuals and families struggling in poverty. This means less spending power, resulting in fewer operations on the market–or a decline of whole demand. The net result is that both the businessman and industrialist are stung, and profits shrink (Hussein, et al., 2023). And if not, social stability and security at large. (ILO, World Employment and Social Outlook Trends 2025, 2025).

As noted by Gerry Rodgers (2020), one of the most pressing challenges in India's labour market is making economic growth more employment-generating. In this context, identifying practical ways to increase labour demand becomes critically important(Rodgers, 2020).

We will only analyze growth in the economy and real wages as they relate to employment. The aim is to find some key insights of the phenomenon and reach useful conclusions that can be used in further studies or researches. The first step hardly looks into man-made GVA and wage growth structure. The second stage explores the linear and nonlinear nexus between structural wage changes, Gross Value Added (GVA) growth and labor growth.

2. Research Problem.

In this research, we tackle the essential question in labor economics. What is the relationship between economic growth, wages, and job creation within the economy?

3. Study's Limitations.

The study did not discuss differences between workers in wages, and how these vary by region, education level, gender, and between permanent and formal/informal employment. This lurks behind numerous contingencies of the character of results. It also did not deal with capital stock and its structural changes. The study setting is confined to the Indian economy 1981-2022.

4. Research Perspective.

The study of the relationship between variables requires a deep comprehension of their evolution. Its most important focus is: GVA Expansion, Economics Dynamics and Real Wages All these dynamics are the key to Where these changes are affecting jobs. The work offers insights into how different linkages have shaped job growth.

5. Literary Studies.

We have two main ways of looking at the connection between wages and jobs. These perspectives will contribute to our analysis and help us better appreciate how differing wage levels are affecting the employment environment. Neoclassical economic theory implies that the raising of the minimum wage should generate lower employment because of two developments: the "scale effect", which occurs when higher prices for goods decrease demand, and the "substitution effect" in which firms substitute cheaper labor with more expensive capital to avoid rising wages. Yet macroeconomic theories suggest that higher wages could lift consumption by low-paid workers and their families. This consumption "multiplier" may help to restore demand, and if so, employment as well. (ILO , Employment effects in different economic theories, 2016).

The India Wage Report emphasizes that very low wages and wage gaps are still the main factors which slow down the achievement of decent working conditions and inclusive growth in India. Based on data from the Employment and Unemployment Survey (EUS), the report reveals that real average daily wages have almost doubled between 1993-94 and 2011-12. It was also noted that rural areas recorded more rapid wage growth than urban areas, while casual workers have been advantaged more than regular workers. Women's wages increased more rapidly than men's, and wages in the unorganized sector grew faster than in the organized sector— all of which are positive developments. However, low wages remain widespread, and wage inequality persists at high levels (ILO, 2018). Haefke et al (2013) highlight that the wages of newly hired workers respond almost one-to-one to changes in productivity, whereas the wages of workers in ongoing employment relationships show a minimal reaction to productivity fluctuations. A key factor in obtaining this result is controlling for cyclical changes in the skill composition of the workforce. These findings confirm the idea that wage rigidity among newly hired workers is the sole explanation for unemployment volatility over the business cycle (Haefke, Sonntag, & Rens, 2013).

According to the role of structural changes in India's labour market, RBI's research indicates during 1980–81 to 2021–22. Employment has shifted away from agriculture towards construction and services, alongside greater workforce regularisation in manufacturing. Employment growth was most pronounced in business services, construction, electrical and optical equipment, and financial services. Across the board, the educational level of the labour force has gone up in every sector. For example, the chemical and machinery sectors, which are capital, intensive industries, have shown to have higher skill levels, fewer casual workers, and more elevated wages. Several service subsectors, namely business and financial services, health, education, and public administration, are characterized by relatively good employment. However, in manufacturing, real wage growth has been lagging behind labour productivity growth for quite some time (RBI, 2024). Moreover, during the period 200012, the growth in India's productivity was mostly due to capital, and there was only a little change in employment restructuring despite the increase in incomes. Labour reallocation occurred mainly within the unorganised sector rather than from unorganised to organised employment, resulting in weak Lewis-type structural transformation and minimal improvement in overall employment quality (Majid, 2019).

The progressive exclusion of less-educated workers from employment, along with slowing employment growth for the educated, were key trends contributing to a declining employment rate, rising unemployment, and, paradoxically, a steady improvement in the average quality of employment. Notably, these deteriorating employment conditions occurred during a period of high economic growth. The primary reason was the "skill-biased" technological change in production, which, driven by accelerating labor productivity growth, was misaligned with demand growth, as reflected in output growth. This is evident from the steadily increasing ratio of labor productivity growth to output growth between 1999 and 2018 (Kumar & Ghose, 2021). Using Shapley decomposition, Aggarwal analyses growth, structural change, and employment linkages in India . It finds that economic liberalisation reduced the role of employment-related structural change in growth, with job creation concentrated in low-productivity sectors despite rising GDP and productivity. This is attributed to trade-driven specialisation and weak inter-sectoral linkages, highlighting the need for strategic state intervention to generate productive employment (Aggarwal, 2018).

Papola (2013) highlighted in his report that while the service sector has been a major driver of recent growth in India, it has experienced a sharp decline in employment elasticity. Additionally, despite a significant rise in exports, the anticipated employment benefits have not materialized. He suggests that a rebalancing of growth, with greater emphasis on the manufacturing industry and a stronger domestic focus, is now essential to enhance the employment potential (Papola , 2013). Also with similar results, Rakesh Kumar (2024) found that India's services-led growth model has not been effective in significantly increasing workforce participation as expected. The gap between national output growth and rising unemployment presents a challenge for policymakers, prompting a need to reconsider and potentially revise India's growth model (Kumar R. , 2024).

Butkus, et al (2023) point out that their analysis, based on data from the European Union over the 2000–2020 period, indicates that tightening labor market regulations would not significantly diminish the potential for economic growth to reduce unemployment. As they point out in his seminal 1962 paper, Okun analyzed U.S. data and found that a 1% increase in GNP was associated with a 0.3 percentage point decrease in the unemployment rate. Numerous subsequent empirical studies have sought to estimate this relationship, known as Okun's coefficient. While most studies acknowledge a clear link between unemployment and economic growth, they differ considerably in their estimates of the magnitude of Okun's coefficient (Butkus, Kacileviciene, Matuzeviciute, Rupliene, & Seputiene, 2023).

Enhanced digital access, geopolitical changes, and climate mitigation efforts are expected to be the three major influences on the employment landscape in India by the year 2030 (World Economic Forum, 2025). The forecasts suggest that to accommodate demographic growth while also factoring in the current employment gaps and the increasing working, age population, India will have to create between 143 and 324 million new jobs by 2050. These figures do not take into account the additional job requirements arising from underemployment and the structural reallocation of labour from agriculture (Singh, 2026). Even a slight reduction in employment in agriculture with a corresponding increase in the construction, services, or manufacturing sectors may result in GDP growth increasing by 0.2 to 0.5 percentage points. Structural reforms that are well, targeted, along with continued public investment, are indispensable to underpin the generation of high, quality employment (Alonso & MacDonald, 2024).

There is a clear gap in the literature in terms of an integrated, sectoral, and growth-linked analysis of how wages interact with GVA growth and structural change to shape employment outcomes in India. Existing studies examine these dimensions largely in isolation, leaving unanswered questions about whether India's growth process is capable of generating sufficiently high-quality, wage-led, and employment-intensive development.

6. Methodology and Data.

The research relies on a set of methodological methods to analyze the interrelationship and effects between the main variables to reach the facts related to the nature of the phenomenon. It uses the (APPF) equation "Aggregate Production Possibility Frontier" to determine the contribution of factors and sectors. Determine the impact of structural changes through a reallocation perspective on labor's wages and productivity. Adopting the ARDL and NARDL methods and the causality test to check the linkages.

All data in the study are from the KLEMS (2024) database, RBI. The economy is divided into only four sub-sectors, which include: (i) agriculture, (ii) traditional industries including construction, energy (Electricity...), and Mining.. (iii) Manufacturing (13 sectors), and (iv) Service (10 sectors). The research relied on dividing the period into four sub-periods to analyze the growth, taking into account pivotal years that included exceptional events, namely the economic reforms of 1991, the global financial crisis of 2008, and the Corona pandemic at the end of 2019.

7. Economic Growth (GVA).

The analysis begins by identifying the main drivers of economic growth through the lens of the aggregate production possibility frontier (PPF). It illustrates the maximum potential output that an economy can achieve given its available resources. It provides insights into productive power, key economic factors, and growth potential.

$$\Delta\ln\ \mathrm{VA} = \bar{v}_{K,j}\left(\Delta\ln\ Z_j + \Delta\ln\ Q_{K,j}\right) + \bar{v}_{L,j}\left(\Delta\ln\ H_j + \Delta\ln\ Q_{L,j}\right) + v_{T,j} \quad \text{.............(7.1)}$$

Where: $\Delta\ln$ VA growth of GVA, Z_j is the accumulated capital, $Q_{K,j}$ is the quality (capital), H_j is labour (number) and $Q_{L,j}$ is labour (quality), $v_{T,j}$ is TFP (level of technology). $\bar{v}_{K,j}$, $\bar{v}_{L,j}$ is he mean input share (two-period) (Reserve Bank of India, 2024).

$$\Delta\ln\ VA = \sum_j \bar{w}_j \Delta\ln\ V_j \quad \text{..(7.2)}$$

Where: V_j is value generated by the sector and $\bar{w}_j$ is the sector's proportion /aggregate, (the bar reflects the mean two years (preceding and current)) (Reserve Bank of India, 2024) (Goldar, et al., 2017).

Table (7.1) lists the factors and sectors that contributed to the increase in the Indian economy's total real GVA. It provides data for Four sub-periods as well as the complete time frame from 1981 to 2022. The table showcases the separate impacts of both the quantity and feature of labor alongside the impacts of both the quantity and type of capital, besides the contribution of sectors.

Table (7.1) Contribution of Factors and Sectors to GVA Growth.

FACTORS AND SECTORS	YEARS	1981-1991	1992-2008	2009-2018	2019-2022	1981-2022
FACTORS	Employment	1.7	1.3	1.1	2.2	1.4
	Labour Quality	0.4	0.3	0.2	0.2	0.3
	Capital Stock	2.5	3.7	4	2.8	3.3
	Capital Composition	0.1	0.2	0.3	0.1	0.2
	TFP VA	0.7	0.7	0.9	-1.5	0.5
SECTORS	Agriculture	0.9	0.7	0.7	0.9	0.8
	Traditional industries	0.7	0.8	0.7	0.6	0.7
	Manufacturing	1.1	1.2	1.3	0.3	1.1
	Services	2.6	3.4	3.9	2.1	3.2
TOTAL	**GVA Growth**	**5.3**	**6.2**	**6.5**	**3.8**	**5.8**

The researcher's calculations are based on the database (RBI). (The numbers rounded)

In general, as shown in the chart and table figures (7.1), economic growth has increased by an average of 5.8% annually. The lowest growth rates were witnessed during the Corona pandemic, i.e. after 2019. The growth rate reached -4% in 2020, then rose to nearly 8% the following year. The highest economic growth rates were during the period 2009-2018, with an average of 6.5%.

Based on the above numbers and figure (7.2), the role of the number of employed individuals in the overall increase in (GVA) had decreased as time has passed except the last while. It accounted for 31,2% of the GVA increase during the period from 1981 to 1991, which declined to 21.2% in the period from 1992 to 2008, and further dropped to 16.3% in the period from 2009 to 2018. After that, it increased to reach 57.3% in the last while. In total, the increase in labor supply contributed approximately 24.5% to the overall GVA growth throughout the entire period of 1981 to 2022.

Improvements in labor quality resulted in an additional 4.6% increase in GVA growth. When taking into account both elements of labor, the annual contribution to the increase in total real GVA was approximately 29.1% from 1981 to 2022.

From 1981 to 2022, the increase in capital stock accounted for approximately 57.4% of the aggregate level GVA growth. From 1981 to 1991, this contribution was 46.8% and then increased to 59.7% from 1992 to 2008. In the last while it reached 71.5%. These figures highlight the big influence of capital inputs on the GVA expansion during the specified time periods. The increase in capital input, considering both quantity and quality combined, contributed over half, approximately 60.8%, to the overall growth of GVA. This indicates that the expansion of capital assets had a big influence on driving the growth.

Chart 7.1 GVA and its Growth

The yearly growth of (TFP) was 13.4% from 1981 to 1991, 11.3% from 1992 to 2008, and 13.9% from 2009 to 2018. After that it decreased to reach -37.8% in the last while. From 1981 to 2022, TFP growth contributed approximately 9.4% to the overall growth of GVA. This indicates the importance of technological advancements, and efficiency improvements, not directly accounted for by labor and capital inputs in driving overall economic growth.

Table (7.1) and Figure (7.2) also illustrates the sector's contribution to the overall (GVA) over time. Specifically, it shows a trend where agriculture's contribution to the increase in GVA has experienced fluctuations. The first period, agriculture accounted for approximately 17.3% of the overall GVA growth. In the subsequent period (1992, 2008), the contribution of agriculture to GVA growth had a major fall, it was only around 11.8%. It is also worth noting that in the very recent period of 2019, 2022, agriculture's contribution to GVA growth went up again, and it was close to 23.2%. These figures reflect the increase of agriculture as a comparative sector and its leading role in GVA expansion over the specified periods.

The services sector has made a significant improvement. In the first period, the services sector contributed about 49% to the growth of GVA. The services sector's contribution to GVA further increased in the period 1992, 2008 reaching approximately 54.5%, this upward trend was thus sustained. The sector's expansion is a clear indication of its continued growth and increasing importance in the overall economy. Besides, the services sector's contribution to GVA has decreased to approximately 54.1% in the recent period of 2019, 2022, this decrease significance recognizes the sector's expanding dominance and thus a growing driver of economic activity. These figures inform us that the services sector has been consistently moving upwards and its contribution to the overall GVA has been increasing. The sector's impressive performance is a reflection of its capability to adjust to the changing market dynamics.

The share of the manufacturing sector in the table had been quite steady over time, with small fluctuations. From the first sub-period to the second one, the contribution of the manufacturing sector to (GVA) declined slightly, from 20.9% to 20.1%. However, the decline in the manufacturing share was much more significant in the last period, when it dropped to 7.2% of GVA growth. Thus, manufacturing's share in total output was significantly lower in crisis and exceptional times. Furthermore, traditional industries kept on contributing less than 12.7% throughout the whole period. Nevertheless, it should be stressed that their contribution in the last sub-period increased to 15.4%.

With the development of societies, the consumption of services usually goes up. This trend can be explained by factors like higher incomes, urbanization, and the change in consumer preferences. The service sector covers various activities such as finance, healthcare, education, and professional services. When the service sector accounts for more than 54% of economic growth, it means that the services offered by these industries have been the main drivers of the expansion. The predominance of services in growth is the direct consequence of the changes in the Indian economy that have been confirmed by numerous studies.

The results reveal that the gross value added (GVA) growth in India is predominantly capital-intensive, with only a small share of human capital contributing to the growth. The services sector, under whose leadership the whole economy is going, these dynamics are becoming more and more visible, and the services sector is playing a vital role in driving growth.

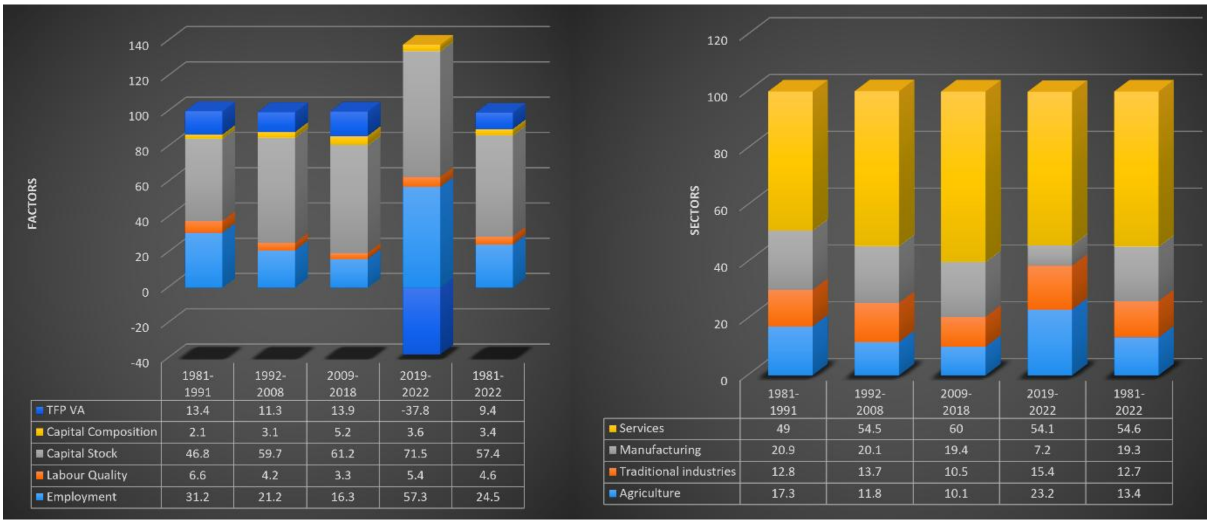


Figure 7.2 Contribution of Sectors and Factors %

8. Labor and Productivity.

The number of workers nearly doubled during the research period, from 290.5 million to 596.6 million over 41 years. Overall, the Indian economy did not achieve high rates of employment during the research period. On average, employment growth over a span of 41 years was approximately 1.77%. However, it is noteworthy that the pattern of employment growth displayed a significant decline, as figure (8.1).

From 1981 to 1991, the average growth was 2.04 %, it stood at 1.53% during the second period, but it dropped to 0.66% between 2009 and 2018. This downward trend in employment growth indicates a decreasing pace of job creation during the specified periods. (Based on the data of KELMS and the calculations conducted by the researcher).

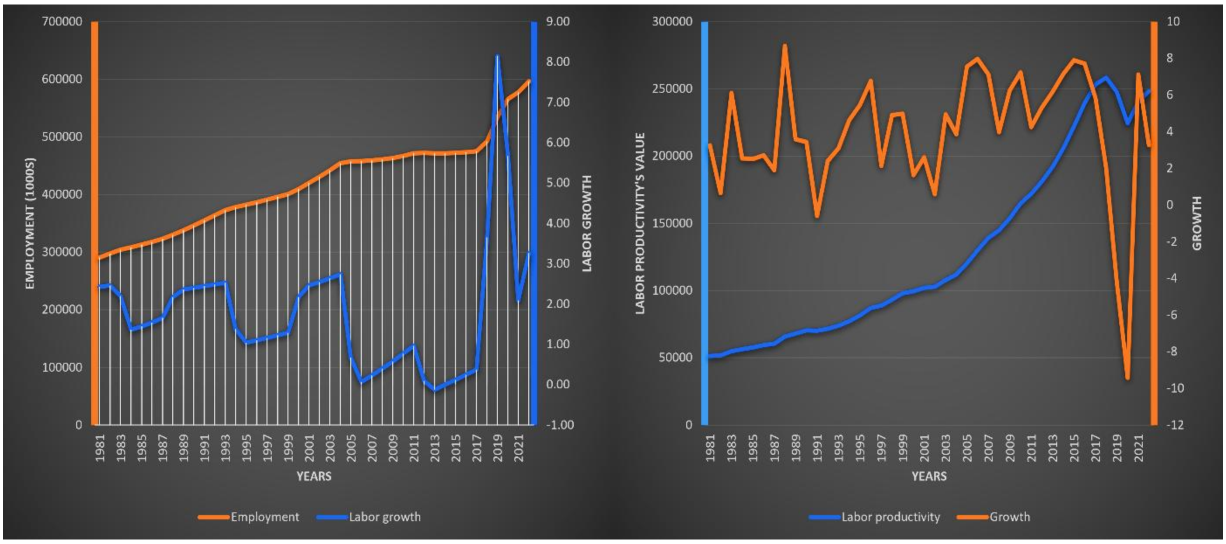


Figure 8.1 Labor (Values – Growth) - Labor Productivity and Its Growth

However, this decline in employment was reversed with a noticeable increase in the recent period (Corona period), with the growth rate reaching 4.79%. But it must be noted that during this period 37% of the job opportunities achieved were in the agricultural sector, 30.8% in services, 20% in the traditional industries sector, and the rest in manufacturing. In comparison with the sectoral job opportunities achieved in the period between 2009 and 2018, agriculture was -109.5%, manufacturing 4%, services 142.9%, and traditional industries 62.6%, out of a total of 29119.4 thousand job opportunities achieved during this period. This indicates structural changes in the job creation between the sectors after Corona. The agricultural sector has played the role of the last and safe haven for job creation in times of crisis. This growth in job opportunities created in the economic sectors after 2019 was not the result of structural changes in investments, as the total net additional capital stock in the recent period was about 83226.73 billion, compared to 197610.21 billion rupees between 2009 and 2018. The share of agriculture in this increase in the recent period was 7.908% compared to 6.426% in 2009-2018. Taking into account the same order for the two comparison periods, we find that the share of manufacturing is 12.834% compared to 14.273%. The share of services is 62.912% compared to 63.253%. The share of traditional industries is 16.344% compared to 16.046%. Similarly, if the growth in the quality of workers is examined as a cause of the growth in job opportunities in the sectors in order to search for a reason behind the growth in job creation in the recent period. The average growth in the quality of workers in the agricultural sector was 0.219% compared to 0.361 in the period 2009-2018. Similarly, the average growth in the quality of workers in manufacturing was 0.448 versus 0.541 and services were 0.530 versus

0.401%, respectively, between the recent period and the previous comparative period. This indicates that the job opportunities achieved in the agricultural sector were driven by its safe nature, which is compatible with the requirements of the quarantine accompanying the crisis.

In contrast to this relatively weak performance in the field of job creation within the economy, there was an outstanding performance in raising productivity levels, as the economy achieved an average growth rate of 3.95% annually during the entire study period, as the figure (8.1).

To illustrate the role of structural changes and the contribution of sectors to productivity growth, the research examines labor productivity, its dynamics, and its growth based on the following equation:

$$\Delta LP_L = \sum \Delta LPi_{Lt} \,.\, li_{t-1} + \sum \Delta li_t .\, LPi_{Lt-1} + \sum \Delta LPi_{Lt} \,.\Delta li_t \quad \text{......}(8.1)$$

Where: LPi_{Lt} is the labor efficiency in the (i) sector in t year, and li_tt is industry labor share of the total, and the symbol Δ is the change (Krishna, Erumban, Das, Aggarwal, & Das , 2017).

As previously mentioned, the initial element in Equation (8.1) represents the influence of productivity changes within individual industries. The second term, referred to as structural change, assesses whether factor inputs are transitioning towards industries with higher productivity levels. The final component in the equation, called the "dynamic reallocation term," it quantifies the collective impact of alterations in factor input distribution and industries' efficiency. Dividing both sides of Eqs. (8.1) by the prior period's labor productivity, we can derive the breakdown of growth.

The findings regarding the growth of total labor efficiency are presented in Table (8.1) through all years and its four sub-periods. The mean yearly expansion of productivity experienced an acceleration, rising from 3.16 % during 1981-1991 to 4.39% during 1992-2008, and further increasing to 5.99% during 2009-2018. These statistics suggest a notable enhancement in labor efficiency, reflecting a rise in levels. But this growth has recently reversed to -0.810% driven by weak economic growth and increased employment growth.

Table (8.1) Total Labor Productivity Growth (reallocation view).

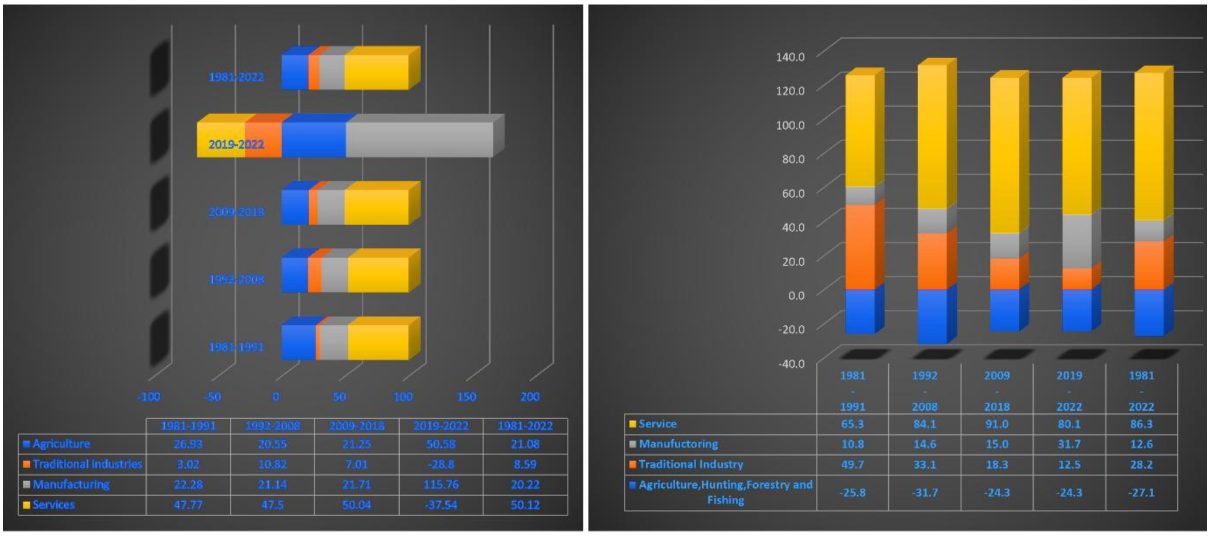
YEARS	LP-WITH	LP- STATIC	LP-DYNAMIC	LP- GROWTH
1981-1991	2.14	1.05	-0.03	3.16
%	67.91	33.10	-1.01	100.00
1992-2008	3.39	0.98	0.02	4.39
%	77.38	22.25	0.37	100.00
2009-2018	4.37	1.62	-0.01	5.99
%	72.97	27.11	-0.09	100.00
2019-2022	-0.055	-0.425	-0.330	-0.810
%	6.759	52.518	40.722	100.000
1981-2022	2.97	1.01	-0.03	3.95
%	75.19	25.69	-0.87	100.00

The researcher's calculations are based on the database (RBI). (The numbers rounded)

Since 1981, there has been a general increase in the structural change effect compared to the 1990s and 2000s. The strength of the static influence has decreased from 33.10% points to 22.25% points, although it subsequently increased to 27.11% during 2009-2018. The favorable static reassignment influence observed in all subperiods indicates a rise in the employment of sectors with rising productivity degrees. The data suggests that productivity expansion typically rises as people transition from low-efficiency to high-efficiency ones, thanks to structural changes. However, these effects were negatively reflected in the recent period, as it witnessed negative growth of -0.425 (52.518%), indicating the transfer of workers from higher production sectors to lower production sectors than they were. But overall, the movement of workers towards higher productivity sectors contributed approximately 25.69% of the growth in total labor productivity over the entire period, The contribution of sectors to the static growth can be seen from the figure (8.2).

While relatively small, the dynamic effect generally remains negative -0.03 (-0.87%). The strength of the dynamic influence has risen from -0.03 (-1.01%) points to 0.02 (0.37%) points, but it declined to -0.01 (-0.09%) during 2009-2018. On the other hand, when analyzing the effects separately, it is evident that the dynamic reallocation effect has been relatively minimal on average throughout the studied period. it means that changes in how labor is allocated across industries, as well as changes in the efficiency of these industries in utilizing labor, are hurting overall labor productivity. that means the industries that previously had high productivity are becoming less efficient, and Labor has shifted from high-productivity industries (e.g., manufacturing) to low-productivity ones (e.g., agriculture).

Within-industry productivity improvement contributes to approximately 75.19% of the productivity expansion through the study's years, with the remainder ascribed to modifications in structure. In the First period, manufacturing and services accounted for approximately 70% of the overall 2.14 points rise in productivity. Specifically, manufacturing contributed 22.28%, while services contributed 47.77% to the expansion. The industrial sector contributed around 3% to the remaining growth rate. Additionally, the agriculture sector contributed approximately 26% to the overall increase in labor productivity during this period. The sector's share ratio did not change much from 2009 to 2018, manufacturing and services accounted for approximately 71% of the overall 4.37 points rise in productivity. But these proportions changed after 2019, with agriculture contributing about 50% and manufacturing about 115% of the negative productivity growth, compared to the opposite contribution of services and traditional industries.



Contribution of Sectors to LP Growth (Within) %   Contribution of Sectors to LP Growth (static)

Figure 8.2 Contribution of Sectors to LP Growth (Within) (static) %

9. The Income Share and Real Wages.

The exploration of labor income share unravels that its changes are predominantly driven by wage variations and labor efficiency. Understanding the interaction between labor participation in income and the synchronization of worker earnings with labor productivity changes is a prerequisite for determining the fairness of employees' share in production growth and hence determining if productivity gains are resulting in wages increases for labor. This highlights the significance of indicators that compare productivity with wages as a means to demonstrate the fairness of such growth.

Chart (9.1) highlights the uneven fluctuations in the labor income share from 1981 to 2022. The value of labor income share at the beginning of the period indicated 0.541, then decreased and became in 2022 about 0.523. While there has been an overall annual reduction of -0.066 percentage points throughout the entire study period, the variations are notable between the different sub-periods. The first two sub-periods demonstrate a reduction in the income share, with 1981–1991 being -0.15 points percentage as average and in 1992- 2008 having a -0.31 points percentage as average sub-period showing a particularly significant decrease. However, the third and fourth sub-period reveals a rise in it, were 0.330, and 0.22 respectively. This indicates that workers' wages did not keep pace with the increase in labor productivity, and therefore workers did not receive their full rights due through wages.

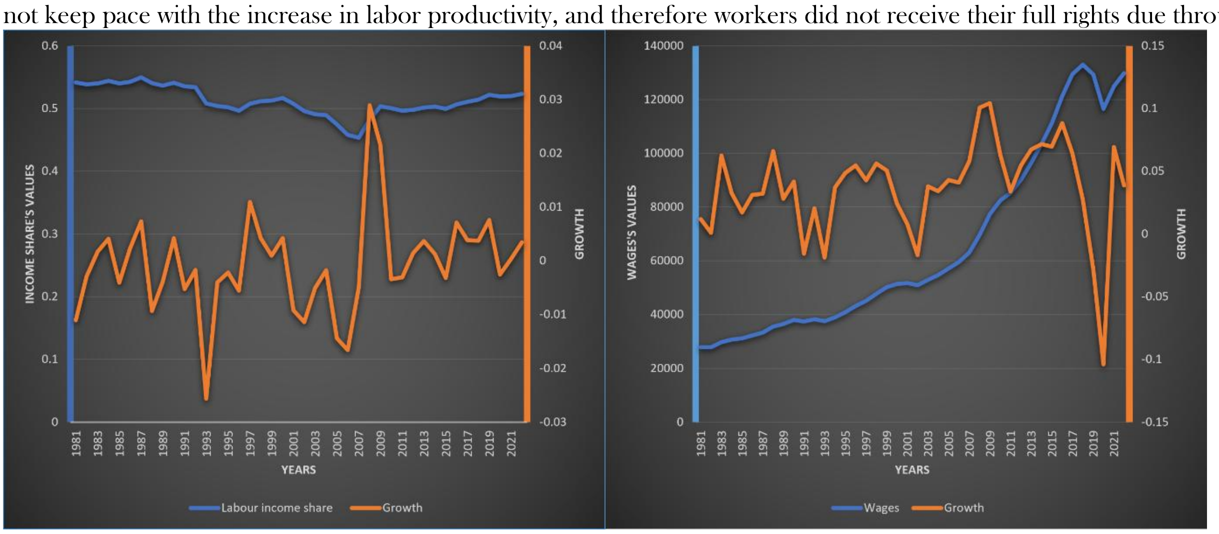


Figure 9.1 Wages and Its Growth - Labor Income Share and Its Growth

This result prompted the study to investigate wages and their growth directly. Highlighting this is necessary: the estimation does not consider changes in worker composition in each sector. It still allows us to analyze and compare the differences between sectors, though. To calculate the real wage rate, the following equations can be applied:

$$W_j = v_j * \frac{L_{isj}}{L_j} \quad \text{...(9.1)}$$

Where: W_j is the real wage average in sector j, v_j is the additional value (constant) in the j, L_{isj} is the labor income share of sector j, L_j is the number of labor in the sector.

The Chart (9.1) shows wages and their growth from 1981 to 2022. The real wage value at the beginning of the period was Rs 27,878 per annum. Then it increased and became about Rs 129,835 per annum in 2022. While there was an overall annual increase of

3.73% throughout the entire study period, differences are noticeable between the different sub-periods. The first three periods show an increase in wages, with the average percentage for the period 1981-1991 being about 2.7%, in the period 1992-2008 it was about 3.77%, and about 6.42% between 2009 and 2018. However, after 2019 revealed a decline in it, as it was -0.35%.

Real wages refer to the share of production earned by workers. Many factors control the increase in wages in the economy, such as the level of experience and education of the worker, the gap between demand and supply in the market, labor pressure groups to determine the minimum wage ..etc. However, at the macroeconomic level, wage growth can be categorized into changes within industries and reallocations between them. To do this, we use a methodology similar to the share of change examination commonly used to study productivity reallocation, as discussed earlier. We conduct separate analyses for different periods. The study examines labor's wages, its dynamics, and its growth based on the following equation:

$$\Delta w_L = \sum \Delta wi_{Lt} \, . \, li_{t-1} + \sum \Delta li_t . \, wi_{Lt-1} + \sum \Delta wi_{Lt} \, . \Delta li_t \text{ ....(9.2)}$$

Where: wi_{Lt} is the labor's wages in the (i) sector in t year, and li_tt is industry labor share of the total, and the symbol Δ is the change. We get a pattern of real wage growth that is very similar to the pattern of labor productivity, but with different growth rates, their relationship can be known through table (9.2).

As we see in Table (9.1), the strength of the static influence has decreased from 40.4% to 25.04% between the first and second sub-period, also it subsequently decreased to 23.55% during 2009-2018. The favorable static reassignment influence observed in all subperiods indicates a rise in the employment of sectors with rising wage degrees. The data suggests that wage expansion typically rises as people transition from low-wage to high-wage ones, thanks to structural changes. However, these effects were negatively reflected in the recent period, as it witnessed negative growth of -0.41 (116.28%), indicating the transfer of workers from higher wage sectors to lower wage sectors than they were. But overall, workers' movement towards higher wage sectors contributed approximately 26.55% of the growth in total labor's wage over the entire period. We can see the share of sectors' participation in the static growth in the figure (9.2).

While relatively small, the dynamic effect generally remains negative -0.03 (-0.88%). The strength of the dynamic influence has risen from -0.1 (-1.9%) points to -0.0003 (-0.01%) points, after that it increased to 0.004 (0.07%) during 2009-2018. In the last sub-period, it became -0.22 (61.83%). On the other hand, when analyzing the effects separately, it is evident that the dynamic reallocation effect has been relatively minimal on average throughout the studied period. it means that changes in how labor is allocated across industries, as well as changes in the wages of these industries in utilizing labor, are hurting overall labor wages. that means the industries that previously had high wages are becoming less, and Labor has shifted from high-wage industries to low-wage ones (e.g., agriculture). This is evident in the last sub-period.

Table (9.1) Total Wages Growth (reallocation view)

YEARS	W-WITH	W- STATIC	W-DYNAMIC	W- GROWTH
1981-1991	1.7	1.1	-0.1	2.7
%	61.4	40.4	-1.9	100.0
1992-2008	2.82	0.94	-0.0003	3.77
%	74.97	25.04	-0.01	100.00
2009-2018	4.90	1.51	0.004	6.42
%	76.38	23.55	0.07	100.00
2019-2022	0.27	-0.41	-0.22	-0.35
%	-78.11	116.28	61.83	100.00
1981-2022	2.77	0.99	-0.03	3.73
%	74.33	26.55	-0.88	100.00

The researcher's calculations are based on the database (RBI). (The numbers rounded)

Wage gains within the industry figure (9.2) accounted for 74.33% of wage growth over the study years, with the rest attributed to structural adjustments. In the first period, manufacturing and services accounted for nearly 85% of the total growth by 1.7 points. Specifically, services contributed 73.17% of the expansion. The industrial sector contributed negative growth by about -16% to the remaining growth rate. In addition, the agricultural sector contributed about 30% to the total increase over this period. However, the sector's share changed significantly from 2009 to 2018, with manufacturing and services accounting for nearly 74% of the total growth by 4.90 points. However, these proportions changed after 2019, with agriculture contributing about -111.6% of the negative productivity growth, compared to the opposite contribution of services, traditional industries, and manufacturing by about 188.11%, 19.2%, and 4.2%, respectively.

Contribution of Sectors to the Wages Growth (Within) % Contribution of Sectors to the Wages Growth (Static) %

Figure 9.2 Contribution of Sectors to the Wages Growth (Within) (Static) %

It is clear that wage increases and productivity growth are linked in the long run (Correlation /87%) and their relationship is significant, this relationship is also evident in all sections of the re-allocation, and it indicates other factors also affect wages (Strain, 2019). Table (9.2) confirms this relationship. Without discussing the causality of the relationship, we can say that in the entire period, wages grew less than productivity (wage = 3.73%/ productivity = 3.95%), and in most sub-periods except for the third period (2009-2018). This period witnessed the lowest employment growth rates, accompanied by the highest growth and productivity rates.

Table (9.2) Correlation- t/Statistic (Probability) Between the Wages and Productivity.

CORRELATION	LP-WITH	LP- STATIC	LP-DYNAMIC	LP- GROWTH
W-WITH	0.831 t/9.47 (0.00)	0.502 t/3.67 (0.0006)	0.220 t/ 1.43 (0.160)	0.82 t/9.141 (0.00)
W- STATIC	0.475 t/3.416 (0.001)	0.978 t/29.89 (0.00)	0.558 t/ 4.259 (0.0001)	0.661 t/5.582 (0.00)
W-DYNAMIC	0.306 t/2.035 (0.048)	0.448 t/3.17 (0.002)	0.780 t/ 7.883 (0.00)	0.394 t/2.719 (0.009)
W- GROWTH	0.836 t/9.64 (0.00)	0.66 t/5.579 (0.00)	0.335 t/2.249 (0.03)	0.87 t/11.19 (0.00)

Because of this gap between productivity growth and wages, research prefers to rely on wages as an explanatory variable for job creation rather than on productivity because the main motivation for workers to move between sectors is the higher wage level regardless of the level of productivity. Of course, within the previously known constraints, such as the worker's competence, experience, and educational level, determine his/her chances of employment.

10. How Variables Interact.

10.1 Linear Relationship (ARDL Model).

All variables are represented as logarithmic differences (changes or growth rates). The conversion to logarithmic differences serves two main purposes: seasonal adjustment of the variables and scaling their magnitudes. Before subjecting the model to the ARDL and NARDL techniques, special attention is given to conducting the Unit Root Test. This step is crucial because the ARDL approach is highly sensitive to lag selection. By employing established information criteria like the Akaike info criterion (AIC), as demonstrated in Table (10.1.1), it is confirmed that all variables exhibit stationarity at the purely (0), purely (1) cointegrated. The correlations among the variables are reported in (appendix, table (1.1) (1.2)).

Table (10.1.1) Unit Root Test (AIC Criteria).

VARIABLE	LAG	LEVEL			FIRST DIFFERENCE		
		Intercept	Trend	None	Intercept	Trend	None
LABOR GROWTH (LG)	5	0.09	0.31	0.39	0.00	0.00	0.00
GVA GROWTH (GVAG)	5	0.00	0.00	0.00	--	--	--
W-WITHIN GROWTH (WWG)	5	0.003	--	--	--	--	--

W- STATIC GROWTH (WSG)	5	0.429	0.72	0.22	0.00	0.00	0.00
W- DY-NAMIC GROWTH (WDG)	5	0.001	0.008	0.0001	–	–	–
W- TOTAL GROWTH (WTG)	5	0.001	–	–	–	–	–

The study intends to highlight the importance of structural changes in wages and their impact on employment. In order to show this, the study figures how wage growth influences the economy through its three main channels. To achieve this goal the study uses the following variables in equation (10.1.1) to find the relationship between them, which is shown in the figure.

$$LG = \beta_0 + \beta_1 GVAG + \beta_2 \text{WWG} + \beta_3 \text{WSG} + \beta_4 \text{WDG} + \varepsilon_t \quad \text{...............(10.1.1)}$$

LG represents the job opportunities (Hussein, et al., 2023), $GVAG$ represents the economic growth (GVA), WWG represents the Wage growth (within), WSG represents Wage growth (Static), WDG represents the Wage growth (Dynamic) (Belman & Wolfson, 2016). β_0 = the regression line's the intercept. The coefficients of the independent variables are $\beta_1, \beta_2, \beta_3, \beta_4$.

Table (10.1.2) provides a concise overview of the form, with the variables accounting for approximately 97% of the observed labor growth, as shown by the R-squared value. The model remains strong even when all unobserved factors are taken into account, as it explains 89% of the labor growth through the descriptive variables, according to the adjusted R-squared. The Durbin-Watson statistic of 2.166, which is within the limits of the 5% confidence threshold, indicates that there is no autocorrelation. These results support the model's consistency and its potential to effectively explain the relationship. The significant Jarque-Bera test allows us to confidently agree with the (H0) that the model does not suffer from abnormal residual distribution issues. Also, the probability F of the LM test, which is higher than the 5% significance level, shows that there is no autocorrelation in the residuals. Moreover, we can accept the (H0) that there is no heteroscedasticity, as both the probabilities of F for the BPG test and ARCH test are significantly higher than the 5% significance level. These findings provide a robust foundation for trusting the model's accuracy and suitability to draw meaningful conclusions from the data. The form has passed all analytical tests, which enhances its reliability and validity for the analysis at hand.

Table (10.1.2) Bound, Model criteria, and Diagnostic test (GVA and wages (Within- Static- Dynamic))

	Bound Test	
F-statistic	4.963	
t-statistic	-4.519	
	Bound critical / F-Statistic (5%)	
Sample Size	**I(0)**	**I(1)**
35	3.276	4.63
40	3.202	4.544
Asymptotic	2.86	4.01
	Bound critical / t-statistic	
Asymptotic	-2.86	-3.99

Model criteria and Diagnostic test

Selected model	ARDL(5,4,4,4,5)	**Durbin-Watson stat**	2.166	**Heteroskedasticity Test: ARCH Prob. F(5,26)**	0.739
R-squared	0.97	**Prob(F-statistic)**	0.0001	**Heteroskedasticity Test: Breusch-Pagan-Godfrey Prob. F(26,10)**	0.325
Adjusted R-squared	0.89	**Jargue- Bera Prob**	0.771	**Breusch-Godfrey Serial Correlation LM Test. Prob. F(5,5)**	0.887

The F-statistic (4.963) and the T-statistic value (-4.519) both exceed the critical values at the 5% significance level, leading us to accept the alternative hypothesis (H1). This implies that the model variables are co-integrated, indicating the being of long-term correlations among the variables. The results present strong evidence supporting the validity and rationality of this relationship in the long term. Here are the two equations representing the model:

Substituted Coefficients:

LG = 0.367* LG (-1) - 0.611* LG (-2) + 0.991* LG (-3) - 1.323* LG (-4) - 1.040* LG (-5) + 0.090* GVAG - 0.330* GVAG (-1) + 0.129* GVAG (-2) + 0.144* GVAG (-3) + 0.492* GVAG (-4) - 0.293* WWG + 0.121* WWG (-1) - 0.075* WWG (-2) - 0.288* WWG (-3) - 0.516* WWG (-4) - 1.512* WSG + 1.180* WSG (-1) - 0.228* WSG (-2) + 1.103* WSG (-3) - 1.656* WSG (-4) + 4.114* WDG - 3.966* WDG (-1) - 2.354* WDG (-2) - 0.939* WDG (-3) + 4.212* WDG (-4) - 6.619* WDG (-5) + 0.052.

Cointegrating Equation:
EC = LG (-1) - (0.201* GVAG (-1) - 0.401* WWG (-1) - 0.425* WSG (-1) - 2.121* WDG (-1))

In the model, all independent variables are statistically significant except for WDG. The findings indicate that changes in GVAG have a favorable influence on LG, while WWG and WSG still exert a negative influence. According to the study's findings, a 1% increase in GVAG in India would result in a corresponding increase of 0.2013 % in the LG, Similar results to ours by (Seyfried, 2011). A 1% increase in WWG and WSG in India would result in a corresponding decrease of -0.401%, and -0.425% in the LG, respectively. The results are similar, with the difference that the study (Neumark and Wascher, 2007) focused on the minimum wage (Neumark & Wascher, 2007). As we can see in Table (10.1.3).

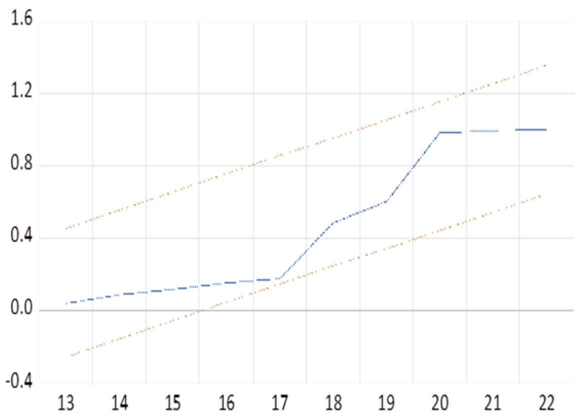
Tabel (10.1.3) Long and Short Run impact (GVA and wages (Within- Static- Dynamic)).

Variable	Coefficient	Prob
	Cointegration Coefficients	
GVA Growth (-1) GVAG	0.2013	0.0749*
W- Growth within (-1) WWG	-0.401	0.00***
W- Growth Static (-1) WSG	-0.425	0.03**
W- Growth Dynamic (-1) WDG	-2.121	0.26
	ECM regression	
CointEq(-1)	-2.617	0.0002***

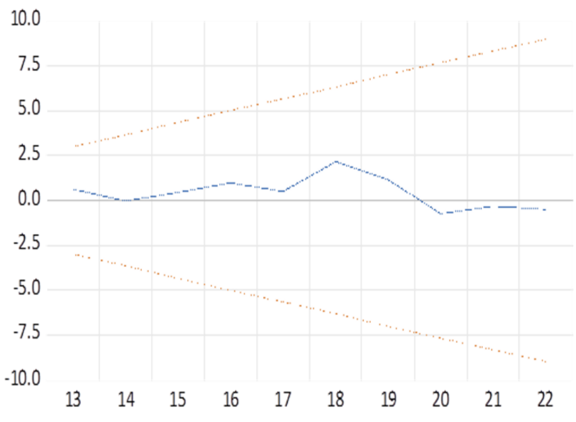
***, **, * Statistically significant when 1%, 5%, and 10% respectively.

Furthermore, the significant negative value observed in the lagged ECT highlights the model's capacity for self-correction and reestablishing equilibrium when confronted with short-term imbalances.

Figure (10.1.1) reveal that the regression coefficients' significance levels do not exceed the 5% cutoff. This finding indicates that the coefficients remain consistent and statistically reliable within the model.



ARDL model (CUSUM of Squares) 5% Significance



ARDL model (CUSUM) 5% Significance

Figure 10.1.1 (CUSUM of Squares) and (CUSUM) 5% Significance

Overall, over the long run, these variables display a harmonious and parallel relationship, showing a consistent and semi-regular pattern of movement between the (LG) and the determinants (GVA and wages (Within- Static- Dynamic)). This relationship is visually depicted in Figure (10.1.2).

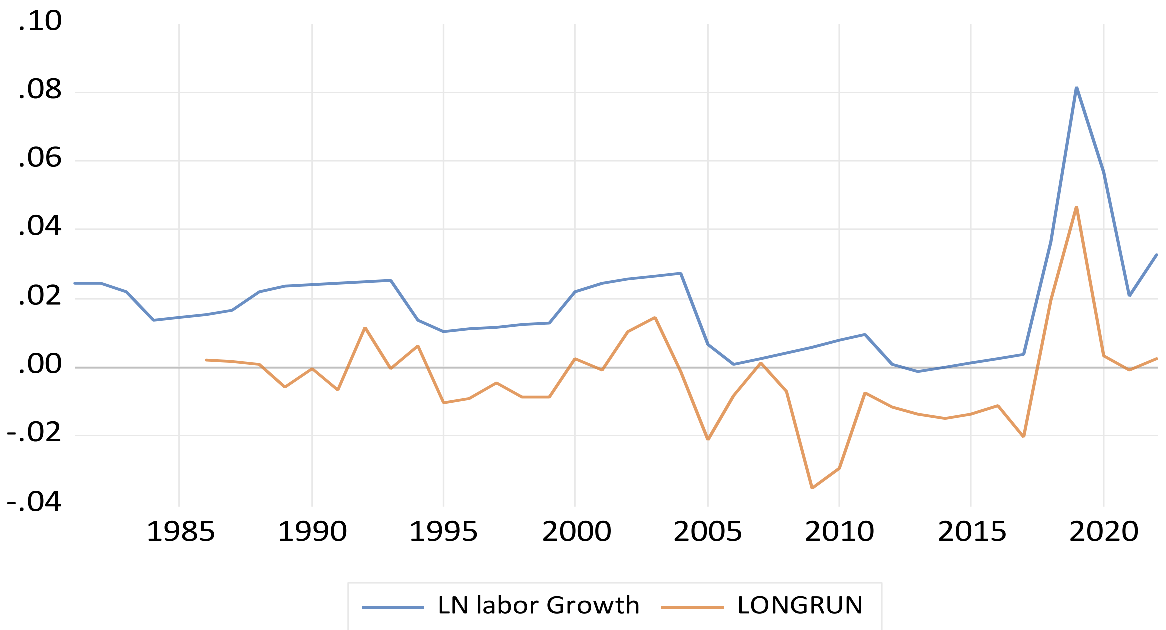


Figure 10.1.2 ARDL model. Long-term relationship (GVA and wages (Within- Static- Dynamic))

10.2 Nonlinear Relationship (NARDL).

We use the same equation but unify the three main parts of wage growth so that the previous equation (10.1.1) becomes:

$$LG = \beta_0 + \beta_1 GVAG + \beta_2 \text{ WTG} + \varepsilon_t \text{ ....(10.2.1)}$$

Where: WTG represents the total wage growth, and the rest of the variables are still as in the previous equation.

Table (10.2.1) offers a summary of the form, with the variables explaining around 95.7% of the observed labor growth, as indicated by the R-squared value. Even when considering all unobserved factors, the model retains its effectiveness, accounting for 85.2% of the Labor growth through the descriptive variables, as reflected in the adjusted R-squared. Moreover, the Durbin-Watson statistic of 2.333, within limits 5% confidence threshold, signifies the absence of autocorrelation. These findings bolster the model's reliability and its capacity to explain the relationship effectively. We can confidently accept the (H0) that the model is free from abnormal residual distribution issues, as evidenced by the significant Jarque-Bera. No signs of autocorrelation in the residuals are observed as the probability F of the LM test is higher than the 5% significance level. Besides, we can also accept (H0) that the variance of the residuals is constant since the probabilities of F for the BPG and ARCH tests are both significantly above the 5% significance level. These findings provide a robust foundation for trusting the model's accuracy and suitability to draw meaningful conclusions from the data. The form has passed all analytical tests, which enhances its reliability and validity for the analysis at hand.

Table (10.2.1) Bound, Model criteria, and Diagnostic test (GVA and wages).

Bound Test		
F-statistic	7.630	
t-statistic	-4.428	
Bound critical / F-Statistic (5%)		
Sample Size	**I(0)**	**I(1)**
35	3.276	4.63
40	3.202	4.544
Asymptotic	2.86	4.01
Bound critical / t-statistic		
Asymptotic	-2.86	-3.99

Model criteria and Diagnostic test

Selected model	(2,5,5,5,4)	**Durbin-Watson stat**	2.333	**Heteroskedasticity Test: ARCH Prob. F(5,25)**	0.902
R-squared	0.957	**Prob(F-statistic)**	0.00046	**Heteroskedasticity Test: Breusch-Pagan-Godfrey Prob. F(25,10)**	0.903
Adjusted R-squared	0.852	**Jargue- Bera Prob**	0.736	**Breusch-Godfrey Serial Correlation LM Test.**	0.138

	Prob. F(5,5)

The F-statistic (7.630) and the T-statistic value (-4.428) both exceed the critical values at the 5% significance level, leading us to accept the alternative hypothesis (H1). This implies that the model variables are co-integrated, indicating the being of long-term correlations among the variables. The results present strong evidence supporting the validity and rationality of this relationship in the long term. Here are the two equations representing the model:

Substituted Coefficients:

LG = 0.510* LG (-1) - 1.414* LG (-2) - 0.087* WTG _POS + 0.0835* WTG _POS(-1) - 0.346* WTG _POS(-2) + 0.106* WTG _POS(-3) - 0.499* WTG _POS(-4) + 0.4009* WTG _POS(-5) - 0.642* WTG _NEG - 0.1071* WTG _NEG(-1) - 0.229* WTG _NEG(-2) + 0.2192* WTG _NEG(-3) + 0.105* WTG _NEG(-4) - 0.431* WTG _NEG(-5) + 0.275* GVAG _POS - 0.017* GVAG _POS(-1) + 0.004* GVAG _POS(-2) - 0.050* GVAG _POS(-3) + 0.209* GVAG _POS(-4) - 0.3530* GVAG _POS(-5) + 0.544* GVAG _NEG - 0.152* GVAG _NEG(-1) + 0.469* GVAG _NEG(-2) - 0.125* GVAG _NEG(-3) + 0.317* GVAG _NEG(-4) + 0.063.

Cointegrating Equation:

EC = LG (-1) - (-0.179883* WTG _POS(-1) - 0.569867* WTG _NEG(-1) + 0.035919* GVAG _POS(-1) + 0.552927* GVAG _NEG(-1)).

Table (10.2.2), all the independent variables are statistically significant except GVAG-POS. The results were relatively consistent with the results of (ARDL model) in terms of the direction of the effect of the variables. The results indicate that changes in GVAG have a positive impact on LG, while WTG still exerts a negative impact. According to the study results, a 1% negative change in GVAG-NEG in India will lead to a corresponding increase of 0.552% in LG. When we observe the positive impact of GVAG - NEG(-1) on labor growth, it may initially seem counterintuitive. However, several economic and structural explanations can clarify this outcome.

Tabel (10.2.2) Long and Short Run impact (GVA and wages).

Variable	Coefficient	Prob
	Cointegration Coefficients	
GVA Growth GVAG - POS(-1)	0.035	0.877
GVA Growth GVAG - NEG(-1)	0.552	0.0914*
W- Total Growth (WTG)- POS (-1)	-0.179	0.0345**
W- Total Growth (WTG)- NEG (-1)	-0.569	0.000***
	ECM regression	
CointEq(-1)	-1.904	0.000***

***, **, * Statistically significant when 1%, 5%, and 10% respectively.

First, while certain sectors of the economy, like manufacturing, experienced a decline in GVA, other sectors, such as agriculture, grew during the same period. The overall labor market could have been better off with a growth of labor, intensive sectors, even if there was an overall decline in GVA. Besides, households and firms might have perceived the GVA decline as a temporary situation and anticipated an economic recovery in the short term, especially after 2019. That optimism could have prompted firms to keep or hire labor in anticipation of good times. At last, the reduction in wages during that period probably had a part in the positive effect, as it was cheaper for firms to raise their labor. A 1% increase in (WTG)-POS and (WTG)-NEG in India will lead to a corresponding decrease of -0.179% and -0.569% in LG, respectively. When we observe a negative impact of both positive and negative total wage growth (WTG - POS(-1) and WTG - NEG(-1)) on labor growth, it suggests that wage changes in the previous period—whether increases or decreases—negatively affect labor growth. This can be explained by some economic views.

Increased total wage growth (WTG - POS(-1)) raises labor costs for firms. As wages rise, firms face higher expenses, making it more costly to hire additional workers. Consequently, labor demand decreases as firms may choose to reduce hiring or delay expanding their workforce. To maintain profitability in the face of rising labor costs, firms often shift to more capital-intensive production methods, and we could note that in the economy (Singh, 2026).

Conversely, a reduced total wage growth (WTG-NEG(-1)) indicates that wages are declining. Although this may appear to be a positive factor in hiring at first. Cutting wages can lower worker morale, reduce productivity, and increase turnover rates. This interaction, in particular, became very obvious after 2019, when the difference between productivity growth (-0.810) and wage growth (-0.35) made it clear why firms might reduce labor demand even if wages were falling. Moreover, when wages go down, workers have less money to spend, which weakens consumer demand. A decrease in demand thus slows down labor growth as firms respond to the drop in demand by cutting back on production and employment. The paradox is that, even though wage changes have had a negative effect on labor growth, employment growth has in fact risen over this period. This seemingly contradictory result can be accounted for by examining the sectoral dynamics of wages and employment. Although wages in sectors went up by 0.27 points, a major reverse migration took place, as workers moved from high, wage sectors to lower, wage sectors, such as agriculture. This transition was mostly a result of the economic upheavals and the quarantine necessities after 2019.

The shift of workers between sectors as a result of limitations during the pandemic showcases how the labor market adjusts. Employees looked for jobs in areas that, although paying less, gave them more stability or quick access to jobs during times of uncertainty. The phrase "Every cloud has a silver lining" can indeed be applied here. Though there were disruptions in sectors that pay

high wages, those that offer low wages, in particular agriculture, have had a flow of workers which consequently has led to employment growth overall.
Furthermore, the significant negative value observed in the lagged ECT highlights the model's capacity for self-correction and reestablishing equilibrium when confronted with short-term imbalances.
Figure (10.2.1) reveal that the regression coefficients' significance levels do not exceed the 5% cutoff. This finding indicates that the coefficients remain consistent and statistically reliable within the model.

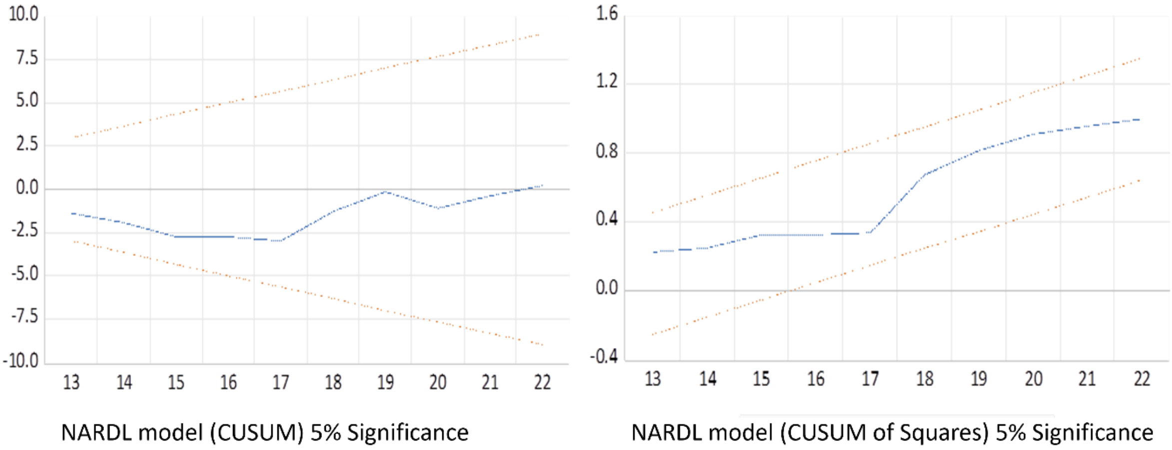


Figure 3.2.1 NARDL model (CUSUM) and (CUSUM of Squares) 5% Significance

10.3 Causality test (Toda-yamamoto).

The models provide the coefficients that tell us how the independent variable responds to changes in another, the Granger causality test goes further, Once the conditions for the causality test are satisfied, lag length, and serial correlation (the appendix for details, table (1.3) and (1.4) figure (1.1)), by determining the direction of causality as:

Table (10.3.1) Causality test (Toda-yamamoto).

SOURCE OF CAUSATION →	LABOR GROWTH (LG)	GVA GROWTH (GVAG)	W- WITHIN GROWTH (WWG)	W- STATIC GROWTH (WSG)	W- DYNAMIC GROWTH (WDG)	ALL
LABOR GROWTH (LG)	--	0.208	0.112	0.00***	0.049**	0.00018***
GVA GROWTH (GVAG)	0.401	--	0.135	0.264	0.0018***	0.00***
W- WITHIN GROWTH (WWG)	0.059*	0.479	--	0.648	0.031**	0.00***
W- STATIC GROWTH (WSG)	0.00***	0.711	0.73	--	0.335	0.00***
W- DYNAMIC GROWTH (WDG)	0.00***	0.981	0.732	0.00***	--	0.0002***

***, **, * Statistically significant when 1%, 5%, and 10% respectively.

Table (10.3.1) tells us, all variables in the long run have a bidirectional causal relationship. We find that GVAG, wage changes, and LG have a bidirectional-causal relationship in the long run. However, the study can conclude that GVAG and wage changes cause LG, but these effects are more pronounced and observable in the long run. In the short run, only WSG and WDG cause LG. In the short run, WDG causes GVAG. Additionally, both WDG and LG have caused WWG. LG also causes WSG, while LG and WSG together drive causes WDG.

Conclusion

Increasing the employment density in Indian society remains one of the biggest challenges that the rapid economic growth led by the service sector is facing. Understanding the factors that influence this remains a key priority to achieve this goal.
The study used linear and nonlinear analyses to capture the effects arising from the interaction of variables. This method was adopted after the study's central question was identified, which was about the impact of economic growth and wage changes on job creation in India. The analysis was done on one dataset (KLEMS (2024) from 1981 to 2022.

Following the first round of tests, the study points out a number of key issues. On the whole, India's economic growth has been based on the intensification of capital and the increase of productivity but the country has been facing the problem of job creation and a clear underutilization of human capital. The structural changes, especially the workers' movement between sectors to better their income, were responsible for more than one, fourth of the wage increase during the period studied. This, therefore, highlights the significance of spreading the job opportunities in the sectors that pay more. In the time after 2019, the final sub-period was characterized by an increase in employment and a reverse migration of workers to lower-paying sectors, especially agriculture. However, this change was not a result of improvements in investment or worker quality; it was a response to the need for job security during the pandemic. It is worth mentioning that wage stability within sectors during this time played a role in labor growth, even though there was a slowdown in economic growth rates. Economic growth was anticipated to have a positive effect on job creation. However, what was surprising is that a slowdown in growth had an even greater positive effect. The explanation lies in the fact that labor-intensive sectors like agriculture took advantage of the slowdown to expand, thus increasing their demand for workers. This is in contrast to the services sector, which is usually the growth driver and is less labor-intensive. The Indian manufacturing sector is like a spectator between cycles of economic boom led by the service sector and downturns (crisis) characterized by the rise of agriculture, remaining largely stagnant.

Our findings are aligned with the neoclassical view that wage increases negatively impact job creation, but this alignment is only partial. The results reveal that wage reductions have a more pronounced negative effect on job creation than wage increases. This suggests that the negative impact of declining purchasing power and aggregate demand in the economy is larger than the negative impact of the trade-off and substitution of labor for capital when comparing their costs in the production process.

Ethical Considerations

This study is based exclusively on secondary macroeconomic data obtained from publicly available and officially published sources, primarily the India KLEMS database and publications of the Reserve Bank of India. No human participants, personal data, surveys, or experiments were involved. Consequently, ethical approval from an institutional review board was not required. The research complies with accepted academic standards of integrity, transparency, and responsible data use.

Author Contributions

- Dr. Ehab Nasief Alabd: Conceptualization, research design, econometric methodology, data analysis, interpretation of results, and drafting of the manuscript.
- Dr. Monica Verma: Literature review, theoretical framing, contextual analysis of India's labour market, manuscript revision, and academic editing.

Both authors reviewed and approved the final version of the manuscript and take full responsibility for its content.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper. The research was conducted independently and without any financial or institutional influence that could affect its objectivity.

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Appendix

Table (1.1) The correlation (ARDL Equation).

Correlation	*Labor Growth (LG)*	*GVA Growth (GVAG)*	*W- within Growth (WWG)*	*W- Static Growth (WSG)*	*W- Dynamic Growth (WDG)*
Labor Growth (LG)	1	-0.447	-0.590	-0.846	-0.651
GVA Growth (GVAG)	-0.447	1	0.782	0.388	0.137
W- within Growth (WWG)	-0.590	0.782	1	0.441	0.425
W- Static Growth (WSG)	-0.846	0.388	0.441	1	0.448
W- Dynamic Growth (WDG)	-0.651	0.137	0.425	0.448	1

Table (1.2) The correlation (NARDL Equation).

Correlation	*Labor Growth (LG)*	*GVA Growth (GVAG)*	*W- Total Growth (WTG)*
Labor Growth (LG)	1	-0.447	-0.716
GVA Growth (GVAG)	-0.447	1	0.770
W- Total Growth (WTG)	-0.716	0.770	1

Table (1.3) Chi-squared test statistics for lag exclusion (Causality test).

VARIABLES	**(LG)**	**(GVAG)**	**(WWG)**	**(WSG)**	**(WDG)**	**JOINT**
LAG 1	93.685	36.827	40.285	49.193	29.8372	169.635
PRO	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]

Table (1.4) VAR Residual Serial Correlation LM Tests (Included observations: 40) (Causality test).

NO SERIAL CORRELATION AT LAG H						
LAG	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	23.217	25	0.564	0.923	(25, 75.8)	0.573
2	34.168	25	0.104	1.4524	(25, 75.8)	0.109
NO SERIAL CORRELATION AT LAGS 1 TO H						
LAG	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	23.217	25	0.564	0.923	(25, 75.8)	0.573
2	58.681	50	0.1871	1.2135	(50, 71.8)	0.223

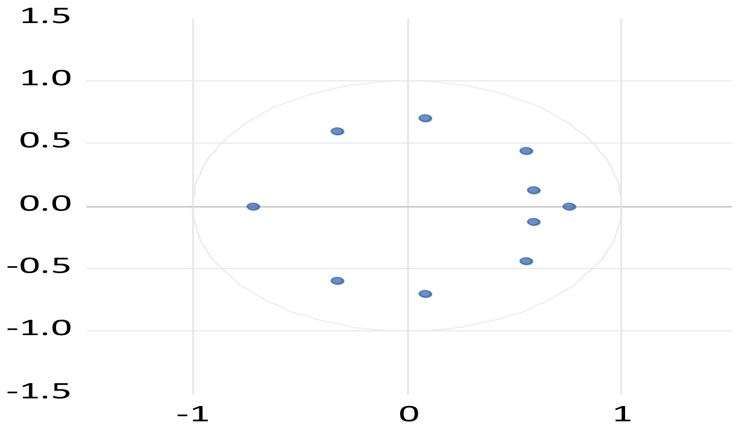

Figure 4 Causality test Inverse Roots of AR characteristic Polynomial (Causality test)