



The Jobless Growth Paradox: Disentangling the Drivers of Industrial Employment in India

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ABSTRACT

This study attempts to examine the structural determinants of industrial employment in India over the period 2000 to 2024 through an OLS regression framework using Newey West HAC estimator. Based on the “jobless growth” hypothesis, the conclusive results of this study highlight an important structural divergence in the labour market. A strong negative relationship is found between manufacturing value added and industrial employment, indicating that recent industrial expansion is being driven by capital intensification and automation rather than labour absorption. In contrast, FDI emerges as an important driver of job creation, indicating that integration into global value chains effectively increases labour demand. Also, the structural analysis makes it clear that the Covid shock was transmitted primarily through a contraction in aggregate demand, rather than through any specific change in labour elasticity.

1. Introduction

India's 21st century economic trajectory is a tale of remarkable expansion and structural contradiction. Since the liberalization reforms of 1991, and especially rapidly since the early 2000s, India has



established its position as one of the world's fastest growing major economies. However, this growth has given rise to an important paradox that has baffled policymakers and economists: the phenomenon of “jobless growth”. While production, capital accumulation and foreign investment have boomed, the rate of labour absorption in the industrial sector has not increased correspondingly. This study aims to experimentally investigate this divergence by analysing the determinants of industrial employment in India from 2000 to 2024. Specifically, it attempts to disentangle the effects of three macroeconomic drivers- manufacturing value addition, foreign direct investment (FDI), and overall economic growth, on the employment share of the industrial sector.

1.1. Industrial Employment: The Stagnating Dependent Variable

Industrial employment serves as the key dependent variable in this analysis, representing the sector's ability to absorb India's emerging workforce. Theoretically, the transition from agriculture to industry is the standard path of economic development, allowing surplus labour to move from low-productivity farming to high-productivity manufacturing (Lewis, 1954). However, recent trends in India show a deviation from this historical norm. Despite a huge demographic dividend with more than 1.20 crore youth entering the workforce annually, the industrial sector's contribution to total employment has remained largely stagnant. The data show that while the absolute number of industrial workers has increased, the share of industrial employment relative to total employment has not seen the structural boom seen in historical examples such as South Korea or China. Instead, India is witnessing a premature shift of labour from agriculture directly to low value services bypassing the formal manufacturing stage. This stagnation is significant because industrial jobs, especially in organized manufacturing, are generally associated with higher wages, social security and skill acquisition (Raveendran & Unni, 2007).

1.2. Manufacturing Value Added: The Engine of Capital Deepening

Manufacturing value added (MVA) as a percentage of GDP is the primary independent variable of this study, which serves as a proxy for the productive capacity and efficiency of the sector. Since 2000, Indian manufacturing has undergone profound transformation characterized by technology upgrading and increased capital intensity. Policy initiatives, ranging from the (National Manufacturing Policy, 2011) to the recent ‘Make in India’ campaign, aim to increase the share of manufacturing in GDP to 25%. However, the relationship between MVA and employment is complex. According to Verdoorn's law (Verdoorn, 1993), faster output growth induces faster productivity growth, often through the adoption of labour saving technologies. In the Indian context, this has manifested as ‘capital intensification’. Firms facing tighter labour regulations and rising wage costs have increasingly opted for automation and



mechanisation. As a result, MVA has shown resilience and growth, driven by capital intensive sectors such as pharmaceuticals, refined petroleum, and automobiles (Goldar, 2000). This value creation has often been the opposite of labour absorption. MVA is important for this study because it allows testing the hypothesis whether modern industrial efficiency acts as a substitute for labour, not a complement.

1.3. Foreign Direct Investment (FDI): The Catalyst for Capacity

The second independent variable, foreign direct investment (FDI) inflows as a percentage of GDP, represents the integration of the Indian industrial sector with global capital markets. Since the early 2000s, India has progressively liberalised its FDI regime, allowing 100% foreign equity in many sectors, including manufacturing. Theoretically, FDI is expected to generate employment through two channels: direct greenfield investment and indirect spillover effects like supply chain linkages. Unlike domestic investment, which may sometimes focus on brownfield modernization (Alker et al., 2000) (upgrading existing machinery without hiring), foreign capital in India has often been directed towards setting up new production units to serve both domestic and export markets (Banga, 2005). Be it global automobile giants setting up hubs in Chennai and Pune or mobile manufacturing units in Noida, FDI brings not only capital but also the need for operational workforce. Therefore, this study establishes FDI as a separate determinant of domestic value addition, which can potentially become a positive driver of employment even during the consolidation of domestic manufacturing.

1.4. Economic Growth: The Aggregate Demand Driver

The final independent variable is the annual growth rate of gross domestic product (GDP), which provides a control for the macroeconomic cycle and aggregate demand. Economic theory suggests a positive correlation between output growth and employment, known as Okun's Law (Okun, 1962), although the coefficient is usually less than one. In a developing economy like India, higher GDP growth should theoretically lift up all sectors, by increasing consumption, stimulating infrastructure development, and creating a general environment of business optimism (Panagariya, 2008).

To analyse these relationships, this study uses ordinary least squares (OLS) regression method. The OLS framework is particularly suitable for this analysis because it provides clear, measurable coefficients that reflect not only the direction of each variable's effect on industrial employment but also its magnitude. Given the varying nature of the independent variables, efficiency (manufacturing value added), capital (foreign direct investments), and aggregate demand (growth), the multiple regression model allows for the interpretation of each factor holding everything else constant.



2. Research Objectives

The primary objective of this study is to empirically examine the structural determinants of industrial employment in India during the post liberalization and reform period (2000–2024). The specific objectives are as follows:

- To analyse the impact of manufacturing value addition on industrial employment, specifically testing the validity of the ‘jobless growth’ hypothesis in the Indian context.
- To examine the role of Foreign Direct Investment (FDI) in employment generation in the industrial sector.
- Investigating the relationship between aggregate economic growth (GDP) and labour absorption to determine whether output growth translates into proportionate job creation.
- To present policy recommendations for increasing the labour-absorptive capacity of the Indian industrial sector on the basis of experimental findings.

3. Hypotheses

- ${}_1H_0$: Manufacturing Value Added has no significant impact on industrial employment in India ($\beta_{mva} = 0$).
- ${}_2H_0$: Foreign Direct Investment inflows have no significant impact on industrial employment ($\beta_{fdi} = 0$).
- ${}_3H_0$: Aggregate GDP growth has no significant impact on industrial employment ($\beta_{gdp} = 0$).

4. Literature Review

The relationship between economic growth, industrial production and job creation remains a central topic in development economics. However, the academic discourse has changed significantly after 2020 period. While earlier literature focused on labour rigidities and regulatory barriers, recent studies have adopted ‘technological displacement’, ‘capital intensification’ and ‘premature deindustrialization’ (Rodrik D. , 2016) as primary drivers of employment trends. This section reviews experimental evidence over the past five years and examines the methodological relevance of ordinary least squares regression in this field.

The paradox of stagnant or declining employment elasticity with high output growth has been rigorously documented in recent years, especially in the Indian context. (Mehrotra & Parida, 2019) have presented a detailed analysis of India's labour market transitions and argued that the period after 2012 represents a distinct phase of ‘jobless growth’ in the manufacturing sector. Their findings suggest that while



manufacturing value added has increased, the absolute number of manufacturing jobs has declined, pushing labour back into low productivity agriculture or the informal service sector.

(Rathore & Khanna, 2021) analysed the impact of the covid-19 pandemic and subsequent recovery on industrial employment. They observed that capital intensive large firms recovered rapidly and expanded market share, while labour intensive MSMEs faced a longer stagnation. Their study highlights a structural break where industrial production is being driven by automation and efficiency and not workforce expansion.

Globally, this trend is supported by (Rodrik & Stiglitz, 2025), who re-examined theory of premature deindustrialization. They advocate that the period of labour-intensive manufacturing export led growth for developing nations is closing due to automation technologies (Industry 4.0). Their analysis suggests that developing economies are peaking in manufacturing employment shares at very low levels of per capita income, unlike early industrializers, such that rising manufacturing value added does not guarantee a proportionate increase in industrial employment.

In contrast to the domestic manufacturing narrative, recent literature on FDI presents a more optimistic but subtle picture. (Harms & Meon, 2014) examined the impact of FDI on employment in emerging economies and found a positive significant relationship. They attribute this to the "greenfield" nature of foreign capital, which often creates the need for the establishment of new production facilities and logistics networks, leading to direct job creation.

In the specific context of South Asia, (Sahoo & Dash, 2017) examined the determinants of employment using panel data and found that FDI inflows had a positive and significant elasticity with employment, while domestic industrial credit showed mixed results. They claim that FDI in India has shifted from pure capital-intensive sectors towards service linked industrial activities, which are relatively more labour absorbent than traditional heavy industries.

The use of advanced econometric techniques such as generalized method of moments or cointegration is common, but the ordinary least squares method remains the cornerstone for estimating employment elasticities because of the interpretability and robustness it provides in small to medium time series.

(Pattanaik & Nayak, 2014) used a log linear OLS model to estimate the employment elasticity of growth in India's secondary sector. Their specification, similar to the one used in this study, regresses log-employment on log GDP and regional value added. He justified the use of OLS on the grounds that for annual macro-variables, regression provides the most direct measure of percentage responsiveness (elasticity), provided stationarity conditions are met. Their results reflected the classic Verdoorn's law,



which showed that output growth was statistically significant but its effect on employment declined over time.

Similarly, (Klasen & Pieters, 2015) used multivariate OLS regression to analyse the determinants of female labour force participation in India. Using independent variables such as GDP growth rates and regional shares, they demonstrated that OLS is effective in isolating the net effect on employment shares of structural variables. Their study highlighted the importance of controlling for aggregate growth (GDP) to avoid omitted variables bias, which validates the methodological choice of including growth rate as a control variable in the present research.

4.1. Research Gap

The existing literature clearly highlights the decoupling of output and employment, but most studies are based on data from 2019 or 2020, that is, before the full post pandemic structural adjustment process. There is very little existing research that simultaneously measures separately the differential effects of manufacturing value addition (domestic efficiency) and FDI (foreign efficiency) within the same OLS framework for the latest period. This study fills this gap by extending the time series to 2024 and offers a contemporary analysis of whether the trend of jobless growth has accelerated or weakened somewhat in the current decade.

5. Methodology

5.1. Data source and period of the study

The study uses annual time-series data covering a period from 2000 to 2024. This time period has been strategically chosen to encompass the post liberalisation mature phase of the Indian economy, the structural shocks arising from the covid-19 pandemic (2020–2021). Data for all macroeconomic variables are taken from the World Development Indicators (WDI) of the World Bank and the Handbook of Statistics on the Indian Economy of the Reserve Bank of India (RBI).

5.2. Theoretical Framework

Traditional theory holds that labour shifts from low productivity agriculture to high productivity manufacturing, but recent evidence suggests that a trend of "capital deepening" has emerged in developing economies. The functional relationship in this context is modelled as follows:

$$\text{EMP}_t = f(\text{MVA}_t, \text{FDI}_t, \text{GDP}_t, \epsilon_t)$$

Where industrial employment (EMP) is a function of domestic production efficiency (MVA), foreign capital capacity (FDI), and aggregate demand (GDP).



5.3. Variable Description

Dependent Variable

Industrial Employment (*ind_empl*): Defined as employment in industry (% of total employment). It measures the labour absorption capacity of the secondary sector.

Independent Variables

Manufacturing Value Added (*mauf_gdp*): Manufacturing value added, as a percentage of GDP. It is a proxy for domestic efficiency and production capacity of the industrial sector.

Foreign Direct Investment (*fdi_gdp*): FDI net inflows, as a percentage of GDP. This reflects the impact of external capital integration and greenfield investments on job creation.

Economic Growth (*gdp_growth*): Annual percentage growth rate of GDP, which is adjusted to control for macro business cycle and demand shocks.

Covid-19 Dummy (*covid_19*): Binary dummy variable, which takes the value '1' for 2020 (pandemic shock) and '0' for all other years, to capture the exogenous structural break resulting from the global lockdown.

5.4. Model Specification

A linear regression model is specified to estimate the elasticity of employment relative to the independent variables. The linear form was chosen because all variables are already expressed in percentage form, allowing direct interpretation of the coefficients as percentage point changes.

The basic econometric equation is expressed as:

$$ind_empl_t = \beta_0 + \beta_1 mauf_gdp_t + \beta_2 fdi_gdp_t + \beta_3 gdp_growth_t + \beta_4 covid_19_t + \epsilon_t$$

Where:

- β_0 is the intercept.
- $\beta_1, \beta_2, \beta_3, \beta_4$ are the coefficients to be estimated.
- ϵ_t is the stochastic error term.

5.5. Stationarity and sample size

At limited sample size (N=25), standard unit root tests (such as Augmented Dickey Fuller) are known to suffer from significant size distortions and low statistical power, often failing to reject the null hypothesis of non-stationarity even when the data are stationary (Schwert, 1989) and (DeJong et al., 1992). Additionally, the variables used (GDP growth, employment share, FDI share) are theoretically bounded ratios or rates, which tend to be mean reverting in the long run. Therefore, to preserve the structural information contained in the levels data, regressions are estimated across levels.

5.6. Estimation Technique and Robustness

Initial diagnosis showed the presence of first-order serial correlation (Breusch-Godfrey Test, $p < 0.05$). To address this violation and ensuring valid statistical inference of classical linear regression model assumptions without biasing the coefficients, the final model was estimated using HAC (Heteroskedasticity and Autocorrelation Consistent) estimator proposed by (Newey & West, 1987). The lag length for the HAC estimator was determined using the automatic Newey-West bandwidth selection criterion. This correction ensures that the reported t-statistics and standard errors are robust to correlation, allowing reliable hypothesis testing.

5.7. Residual and Model diagnostics

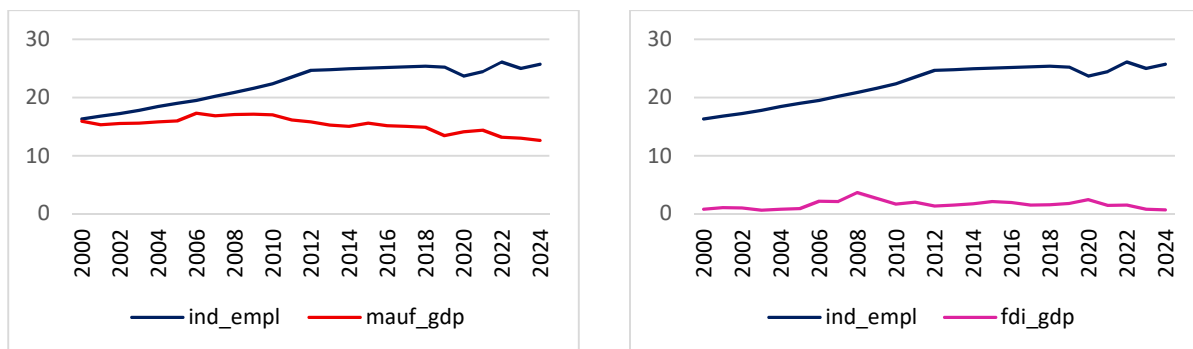
- Breusch-Godfrey test for serial correlation
- Jarque-Bera test for Normal distribution of residuals
- Breusch-Pagan-Godfrey test for heteroskedasticity
- Variance Inflation Factor (VIF) for multicollinearity

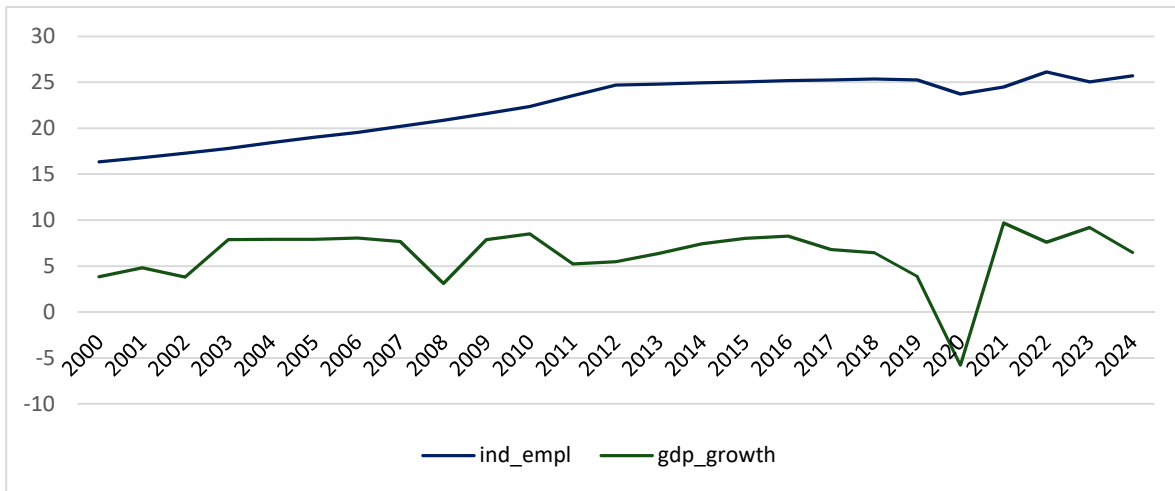
6. Analysis and discussions

6.1. Trends in Industrial employment in India since 2000

Figure 1 displays India's industrial employment share against manufacturing value added share, FDI and overall GDP growth over 2000–2024. Industrial employment grows slowly while manufacturing value addition remains stagnant around 15-20%, indicating weak labour absorption in manufacturing expansion. Industrial employment is upward with foreign direct investment, which is less volatile but positively correlated. Industrial employment grows steadily; There is instability in GDP growth with the pandemic crisis.

Figure 1: Trends in Industrial employment in India 2000-2024





Source: compiled from World Bank development indicators and RBI handbook of statistics

6.2. Descriptive Statistics

Table 1 presents the summary statistics for the dependent and independent variables over the study period (2000–2024).

Table 1: Descriptive Statistics

Statistic/variable	ind_empl	mauf_gdp	gdp_growth	fdi_gdp
Mean	22.37	15.33	6.26	1.58
Median	23.70	15.56	7.41	1.52
Maximum	26.12	17.30	9.69	3.62
Minimum	16.32	12.61	-5.78	0.61
Std. Dev.	3.27	1.31	3.08	0.71
Skewness	-0.58	-0.44	-2.47	0.85
Kurtosis	1.81	2.50	10.33	3.90
Jarque-Bera	2.91	1.06	81.39	3.82
Probability	0.2338	0.5899	0.0000	0.1478

The average share of industrial employment (ind_empl) over the last two decades has been 22.37%, with a maximum recorded at 26.12%. This shows that despite India's rapid growth journey; the industrial sector provides employment to less than one-fourth of the total workforce. Manufacturing value added (mauf_gdp) averaged 15.33%, reflecting the sector's stagnant contribution to national output. Economic Growth (gdp_growth) exhibits the highest volatility, with a standard deviation of 3.08. The range is



drastic, spanning from a high of 9.69% to a historic low of -5.78%, capturing the severe contraction induced by the covid-19 pandemic. In contrast, FDI inflows (*fdi_gdp*) have remained relatively stable but low, averaging 1.58% of GDP.

Jarque-Bera test results show that *ind_empl*, *mauf_gdp*, and *fdi_gdp* follow normal distribution ($p > 0.05$). However, *gdp_growth* is not normally distributed ($p < 0.01$) and highly leptokurtic (Kurtosis = 10.33), statistically expected due to the extreme abnormal value of the 2020 pandemic shock. While OLS assumes normality of residuals in independent variables such as growth is acceptable, especially when driven by known structural breaks.

6.2. Correlation Analysis

Table 2: Pairwise Correlation Matrix

Variable	<i>ind_empl</i>	<i>mauf_gdp</i>	<i>gdp_growth</i>	<i>fdi_gdp</i>
<i>ind_empl</i>	1.0000			
<i>mauf_gdp</i>	-0.5466	1.0000		
<i>gdp_growth</i>	0.0897	0.1117	1.0000	
<i>fdi_gdp</i>	0.2191	0.4164	-0.2885	1.0000

Table 2 displays the pairwise correlation matrix to examine the linear associations between the variables. The most notable observation is the strong negative correlation (-0.55) between manufacturing value added (*mauf_gdp*) and industrial employment (*ind_empl*). This provides initial statistical evidence for the "jobless growth" hypothesis. This suggests that as the output share of the manufacturing sector increases, the employment share tends to decrease, pointing towards capital intensive production patterns. On the other hand, foreign direct investment (*fdi_gdp*) shows a positive correlation (0.22) with industrial employment. This shows that foreign capital inflows are associated with job creation, possibly due to the establishment of new production capacities. The correlation between *gdp_growth* and *ind_empl* is positive but significantly weak (0.09). This indicates that overall economic growth does not automatically translate into proportionate job creation in the industrial sector, stressing the need for structural policy interventions beyond mere growth stimulation.

6.3. Regression Results

The regression results in table 3 highlight important structural relationships in the Indian industrial sector.

Table 3: Regression model results (HAC Corrected)

Variable	Coefficient (β)	Std. Error	t-Statistic	Prob.	Sig.
Constant (C)	48.21	3.97	12.15	0.0000	***
mauf_gdp	-2.18	0.38	-5.76	0.0000	***
fdi_gdp	3.21	1.04	3.09	0.0058	***
gdp_growth	0.41	0.16	2.65	0.0153	**
covid_19	0.07	0.86	0.08	0.9353	NS
R-squared	0.67	Mean dependent var	22.37		
Adj. R-squared	0.60	S.D. dependent var	3.27		
F-statistic	10.13	Prob(F-statistic)	0.0001		
Wald F-stat	10.35	Observations	25		

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable: Industrial Employment (ind_empl)

The coefficient of *mauf_gdp* was found to be negative and highly statistically significant ($\beta = -2.18$, $p < 0.01$). A one percentage point increase in the share of the manufacturing sector in gross domestic product (GDP) is associated with a 2.18 percentage point decline in the industrial employment share. This confirms the central hypothesis of Jobless Growth, indicating that industrial output expansion is driven by capital-based technological progress and automation rather than labour absorption.

The coefficient of *fdi_gdp* was found to be positive and statistically significant ($\beta = 3.21$, $p < 0.01$), means that a one percentage point increase in net foreign direct investment (FDI) inflows is associated with a 3.21 percentage point increase in industrial employment. This indicates that unlike domestic output growth, foreign capital inflows, possibly in the form of new industries (Greenfield Projects) play a dominant role in net new job creation.

gdp_growth was found to have a positive impact on industrial employment ($\beta = 0.41$, $p < 0.05$). Although economic expansion creates employment, its elasticity is less than one, which indicates that it is not possible to solve the problem of unemployment on the strength of growth alone, unless it gets structural policy support.

The dummy variable *covid_19* was found to be statistically insignificant ($p = 0.93$). This insignificance means that the sharp contraction of *gdp_growth* in 2020 (which fell by -5.8%) had already mathematically absorbed the impact of the pandemic. This shock was transmitted primarily through a



decline in aggregate demand (GDP), rather than through any independent structural change in the employment-production relationship.

6.4. Model fit and validity.

The R squared value is 0.67, indicating that approximately 67% of the variation in industrial employment is explained by the independent variables (Manufacturing Value Added, FDI, and Economic Growth). Considering the complexity of macroeconomic labour markets, this represents a strong fit. The Adjusted R-squared of 0.60 confirms that the model is robust and not overfitted, even with the inclusion of the covid-19 dummy. The F-statistic of 10.13 is highly significant with a probability value of 0.0001 ($p < 0.01$). This confirms that the independent variables, taken together, have a statistically significant relationship with industrial employment. We reject the null hypothesis that all slope coefficients are zero. Although time-series data often suffer from serial correlation, the use of the Newey West HAC estimator ensures that the standard errors are corrected. This validates the significance of the t-statistics reported in Table 3, making the findings reliable for policy formulation.

6.5. Model Diagnostics

To ensure the statistical validity of the regression estimates, several diagnostic tests were conducted. The first and most important check for multivariate models is to assess multicollinearity between independent variables (table 4)

Table 4: Variance Inflation Factors (VIF)

Variable	Coefficient Variance	Uncentered VIF	Centered VIF	Result
gdp_growth	0.0245	5.82	3.92	No Multicollinearity
mauf_gdp	0.1437	265.18	2.72	No Multicollinearity
fdi_gdp	1.0784	34.95	2.39	No Multicollinearity
Constant	15.7458	137.42	NA	--

The Centered VIF values for all independent variables range between 2.39 and 3.92. These values are well below the conservative threshold of 5.0 recommended by (Hair et al., 2010) and significantly below the looser threshold of 10.0, following the diagnostic framework established by (Marquardt, 1970) to assess the independence of predictors. This indicates that the variables, manufacturing value added, FDI, and GDP Growth are sufficiently independent of each other, ensuring that the regression coefficients reported in Table 3, isolate the specific impact of each variable on employment effectively.

6.6. Residual statistics

A fundamental assumption of OLS regression models is that the residuals must follow a normal distribution.

Table 5: Normality of Residuals (Jarque-Bera)

Metric	Value	Interpretation
Skewness	0.47	Near Symmetry (0)
Kurtosis	2.79	Near Normal (3)
Jarque-Bera	0.9800, p = 0.61	Fail to reject H_0

The Jarque–Bera statistic (table 5) is 0.9800 with a corresponding probability value of 0.61. Since the p-value is significantly greater than the 0.05 significance level, we fail to reject the null hypothesis of normality. This confirms that the error terms are normally distributed, ensuring that the standard errors and confidence intervals calculated in the regression are statistically valid.

To confirm that the variance of the t terms is constant (homogeneity), the Breusch Pagan Godfrey test was performed.

Table 6: Heteroskedasticity Test (Breusch Pagan Godfrey)

Test Statistic	Value	(p-value)	Conclusion
F-statistic	0.7130	0.5927	Fail to Reject H_0
Obs*R-squared	3.1201	0.5379	Homoscedastic
Scaled Explained SS	1.7898	0.7743	Fail to Reject H_0

The null hypothesis of the test is that the residuals are homogeneous. Obs*R-squared statistic (table 6) is 3.1201 with p-value 0.5379. Since $p > 0.05$, we fail to reject the null hypothesis. This confirms that the variance of the residuals remains constant over the sample period and that there is no heteroskedasticity problem in the model.

7. Conclusion

This study highlights a serious divergence in the labour market, often described as ‘jobless growth’. Regression analysis involving Newey West HAC standard errors confirms that the negative elasticity between manufacturing value added and industrial employment is highly statistically significant. This finding supports the hypothesis that India's recent industrial expansion has been driven primarily by capital deepening and automation, rather than labour absorption, which is consistent with the theory of



premature deindustrialisation. In contrast, foreign direct investment (FDI) proves to be a major engine of job creation, showing a strong and positive impact on industrial employment. This suggests that integration into global value chains through greenfield investments effectively expands labour demand. The impact of macroeconomic growth was also found to be positive on employment, but its magnitude is not sufficient to solve the challenge of unemployment. In particular, the statistical insignificance of the covid-19 dummy variable indicates that the impact of the pandemic on employment manifested primarily through a sharp contraction in aggregate demand, rather than any isolated structural change in labour elasticity. Based on these findings, policymaking now needs to move away from solely production-based incentives towards employment centric frameworks. Also, investment promotion strategies should target greenfield FDI for setting up new production hubs and provide fiscal support to labour-intensive micro, small and medium enterprises (MSMEs), thereby translating India's economic growth into equitable and robust job creation.

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