Graduate Unemployment in India (2011–2023): An Empirical Analysis of Labour-Market Determinants and Policy Implications

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ABSTRACT

This paper investigates the key macroeconomic and structural factors driving graduate unemployment in India from 2011 to 2023. Using Fixed Effects Panel Data Regression, supported by Ridge Regularization, it examines the impact of government expenditure on higher education, GDP growth, higher education enrolment (GER), labour market informality, sectoral employment trends (services and industry sectors), and regional income disparities (NSDP per capita) on the aggregate graduate unemployment rate.

Findings reveal that GDP growth, public spending on higher education, labour market informality, and services sector employment are positively and significantly associated with graduate unemployment, suggesting jobless growth and inefficiencies in public investment. Industrial sector employment has a negative effect, highlighting its role in graduate job absorption. GER and NSDP per capita are statistically insignificant, which suggests that higher education access and income levels alone do not ensure better graduate employment outcomes.

The study recommends evidence-based policies that promote skill-based training, better industry-academia linkages, formalization of jobs, and inclusive industrial growth to address underemployment and harness India's demographic dividend.

INTRODUCTION:

The issue of rising graduate unemployment has emerged as a critical socio-economic challenge in India, a nation that boasts one of the largest higher education systems in the world. Despite India's rapid expansion in higher education, graduate unemployment has continued to rise, creating pressing challenges for policymakers and young professionals. This paper explores the underlying causes of this trend by examining the relationship between graduate unemployment rates and key macroeconomic and structural factors such as government expenditure on higher education, economic growth (GDP growth), higher education enrolment (Gross Enrolment Ratio – GER), labour market informality, sectoral employment trends (services and industry sectors), and regional economic disparities (NSDP per capita).

While exploring these key factors, the study also discusses many related aspects such as quality of education, job market saturation, regional employment trends, skills mismatch, and skills enhancement all of which influence these macroeconomic determinants and shape graduate employment outcomes.

The topic derives its significance from the fact that the rising unemployment among university graduates is not only an economic issue but also a social and developmental challenge, as it reflects a potential mismatch between the education system and the labour market in India. Despite significant public investments, it is unclear whether India's higher education system has translated into improved graduate employability. The continued rise in graduate unemployment alongside rising GER points to phenomena like job market saturation and persistent skill mismatches.

This research is particularly relevant as it investigates the impact of various macroeconomic and structural factors on graduate unemployment trends using macroeconomic and state-level data from 2011 to 2023. To fully harness its demographic dividend, India must align higher education policies with evolving labour market needs. If these structural issues remain unaddressed, they could lead to wasted human capital, prolonged underemployment of graduates, and reduced economic productivity, hampering the long-term development of the country. This paper aims to provide empirical evidence on the root causes of rising graduate unemployment and suggest policy recommendations that can bridge the gap between higher education and employment in India.

This paper focuses on answering the central research question:

What are the key factors contributing to the rising unemployment rate among university graduates in India?

The hypotheses associated with this question are as follows:

Null Hypothesis (H_0):

None of the identified factors (government expenditure on higher education, GDP growth, higher education enrolment, labour market informality, sectoral employment trends, and regional economic conditions) have a statistically significant impact on the rising unemployment rate among university graduates in India.

Alternative Hypothesis (H_1):

At least one of the identified factors has a statistically significant impact on the rising unemployment rate among university graduates in India.

These hypotheses guide the choice of variables and methodology. By analysing the significance and economic implications of these factors, the study aims to identify which variables drive graduate unemployment in India and to what extent.

The independent variables in this study are drawn from established economic theories and past literature. Human Capital Theory supports the inclusion of government expenditure on higher education which is expected to enhance skills and reduce graduate unemployment. Still, its effectiveness depends on how well investments are aligned with industry needs. It also guides the inclusion of the Gross Enrolment Ratio in higher education (GER) which states that increased access to higher education must reduce unemployment, while Okun's Law underpins the use of GDP growth. However, research suggests the presence of jobless growth, where economic expansion does not necessarily translate into better employment opportunities for graduates.

Labour market informality which is a significant factor in graduate employment outcomes in a developing country like India, reflects structural inefficiencies where graduates are absorbed into precarious, informal jobs, limiting formal employment opportunities. The employment shares of the services and industry sectors are included in this study to capture sectoral absorption trends, as both industries are key graduate employers in India. Given India's structural shift toward a service-oriented economy and industrial reforms such as 'Make in India,' these sectors are crucial for understanding graduate absorption trends. Net State Domestic Product (NSDP) per capita serves as a proxy for regional disparities, though literature suggests its effects on graduate employment patterns are mixed.

To address the research question, this paper uses **Fixed Effects Panel Data Regression** across **33 Indian regions** (28 States and 5 Union Territories) from **2011 to 2023**, supported by Ridge Regularization to address multicollinearity. This econometric approach controls for unobserved, time-invariant state-specific factors, focusing on within-state income variations over time. Hypothesis testing answers the research question by assessing the statistical significance of the coefficients, while robustness checks strengthen the results. Qualitative Analysis complements the quantitative findings by offering contextual insights into the structural and institutional factors affecting graduate employability.

This paper is structured into five comprehensive sections:

Section 1 - Introduction:

Outlines the research question, motivation, significance, and methodological approach.

Section 2 - Literature Review:

Reviews relevant literature, identifies theoretical frameworks and their Indian context and highlights research gaps.

Section 3 - Methodology:

Details the data sources, variable selection, and econometric methods, including robustness checks used in the analysis.

Section 4 - Data Analysis:

Presents descriptive statistics, regression outcomes, hypothesis testing, robustness checks, qualitative analysis, and interpretation of results. Also discusses the implications of the study and its limitations.

Section 5 - Conclusion

Concludes with a summary of findings, policy recommendations, and directions for future research.

The study finds that labour market informality, services sector employment share, and government expenditure on higher education are positively associated with graduate unemployment, while industrial sector employment shows a negative relationship. The GDP growth rate unexpectedly displays a positive correlation with graduate unemployment, indicating jobless growth. On the other hand, Gross Enrolment Ratio and NSDP per capita do not exhibit statistically significant relationships. These findings form the foundation for the qualitative themes and policy recommendations explored in later sections.

This study contributes to the literature by providing empirical evidence on the key macroeconomic and structural determinants of graduate unemployment in India, addressing the paradox of jobless growth and higher education oversaturation. It offers data-driven policy recommendations to realign higher education outcomes with labour market demands and sectoral absorption patterns. By ensuring methodological rigor and a coherent structure, this paper aims to generate actionable insights to inform labour market reforms and national strategies aimed at reducing graduate unemployment, fostering inclusive economic development, and leveraging India’s demographic dividend.

LITERATURE REVIEW:

This section critically reviews empirical studies on graduate unemployment, structured around themes such as higher education expansion and economic growth, and identifies empirical gaps that this study addresses.

The review includes studies that:

- Analyse the relationship between higher education and graduate unemployment.
- Investigate macroeconomic determinants of graduate unemployment.
- Assess labour market and regional dynamics affecting graduate employability.
- Provide empirical evidence relevant to the Indian economy.

The review excludes studies that:

- Do not differentiate between graduate and general unemployment.
- Lack empirical evidence or statistical analysis.
- Are based on labour markets fundamentally different from India's.

This review aims to establish a solid foundation of knowledge around the topic to provide a comprehensive background to the readers and enable them to effectively draw comparisons with this study's outcomes.

The literature can be organized around the following themes:

Higher Education Expansion and Its Impact on Graduate Unemployment:

Empirical studies show that higher education expansion does not always lead to lower unemployment, particularly when labour market absorption is weak.

Chakraborty (2019) in his study using panel data regression on Indian state-level data, found a positive correlation between GER and unemployment, indicating that higher education alone does not ensure employability. However, his study lacks control for sectoral employment trends.

Pothan & Yadav (2019) use survey data to examine the impact of India's higher education expansion on the labour market, finding that an oversupply of graduates with similar qualifications has intensified job competition. They highlight a growing mismatch between graduates and available opportunities, particularly in fields where job creation has lagged behind educational expansion. However, their reliance on survey data limits the study's ability to capture long-term employment trends and differences in skill mismatches across industries.

Agarwal & Kumar (2020), using longitudinal labour market data, found that while higher GER has expanded education access, it has not improved employability, as many graduates lack industry-relevant skills. However, their study does not account for regional economic disparities.

These studies reveal that while GER has increased, employability remains limited due to oversaturation and poor labour market alignment — issues this study addresses.

Government Expenditure on Higher Education and Graduate Employment:

Public investment in higher education is crucial for enhancing human capital and employability, though its effect on employment depends on how efficiently funds are allocated and utilized.

Rao (2021), using state-level regression analysis, analysed government spending patterns on higher education across Indian states and found a weak but positive correlation with graduate employment rates, suggesting that increased funding alone does not guarantee improved employment outcomes unless accompanied by quality-enhancing reforms. However, the study does not explore the ways of quality enhancement and the role of public-private universities.

Mukherjee (2020), through a qualitative policy review, focusing on the post-NEP 2020 landscape, found that increased government spending allocations to professional and technical institutions led to marginal improvements in graduate absorption, particularly in the services and industrial sectors. Nonetheless, the study lacks an exploration of the industry-specific employment patterns.

Gupta (2019), applying panel data regression across states from 2005 to 2018, found that while states with larger per-capita higher education spending exhibit lower graduate unemployment, the effect is contingent on complementary factors such as infrastructure quality and labour market demand. However, Gupta's study does not capture the role of labour market dynamics in influencing graduate employability.

Though public spending shows some promise, its effect on graduate employability remains unclear without concrete analysis — this study explores that connection explicitly.

Quality of Education and Graduate Employment Outcomes:

While increasing higher education enrolment is important, educational quality remains a key concern.

Mehta & Sinha (2021), using institutional performance data and employer feedback surveys, found that higher education institutions in India often fail to equip graduates with market-relevant skills. Poor faculty training, outdated curricula, and limited exposure to real-world applications reduce graduate employability. However, their study does not differentiate between public and private institutions, making their role unclear in influencing employability.

Gupta (2019) conducted a longitudinal study on graduate employment rates, finding that education quality measured by accreditation levels, faculty credentials, and research output strongly correlates with employability. The rank of the institution also matters significantly. However, his study does not consider socioeconomic factors, such as access to quality education based on income disparities.

Education quality significantly affects job readiness, but institutional and socioeconomic disparities are underexamined — this study highlights those dimensions through secondary and qualitative insights.

Skills Mismatch and Employability:

Skills mismatch i.e., the misalignment between the skills imparted by educational institutions and those demanded by the labour market, often leads to underemployment of graduates.

Aggarwal & Thakur (2018), using survey-based employer assessments, found that a significant proportion of Indian graduates lack essential employability skills, particularly in problem-solving, communication, and industry-specific technical expertise. Their study highlights that curriculums are outdated and misaligned failing with labour market needs. However, their research focuses primarily on urban employment markets, leaving gaps in understanding how skills mismatches affect rural or semi-urban graduates.

FICCI (2019) analysed corporate hiring trends across industries and found that while India produces a large number of graduates annually, many employers struggle to find candidates with job-ready skills. Their report attributes this issue to limited industry-academia collaboration, where universities fail to incorporate practical, skill-oriented training into their curricula. However, the study does not provide evidence-based policy recommendations to combat the impact of this skills mismatch on graduate employment.

These studies highlight that skills mismatch is a key barrier to graduate employability, however, they fail to account for sectoral and regional variations and suggest effective policies — gaps this study addresses through a mixed-methods approach.

Economic Growth and Graduate Employment: The 'Jobless Growth' Debate:

While economic growth is believed to reduce unemployment, India has experienced jobless growth, where output increases have not translated into proportional job creation.

Dasgupta & Singh (2020), using macroeconomic employment elasticity analysis, found that India's high GDP growth has not significantly reduced graduate unemployment. Their study attributes this to the dominance of capital-intensive industries, which generate fewer jobs per unit of output for graduates. However, their analysis lacks sectoral disaggregation, making it unclear which industries contribute most to jobless growth.

Saha (2021) conducted a macro-level panel data analysis and found that while India's economic growth has expanded formal sector output, it has not resulted in a corresponding rise in graduate employment. The study attributes this to a structural shift toward automation and digitalization, which reduces the demand for traditionally skilled graduates. However, Saha's analysis does not account for the role of informal employment, which may be absorbing a portion of unemployed graduates.

Kannan & Raveendran (2019) examined the relationship between GDP growth and employment generation in India, concluding that GDP's employment elasticity has declined. While service-sector growth has created jobs, many are informal and not suited for graduates. However, their study does not account for educational qualifications in employment trends, limiting its relevance to graduate job seekers.

Existing research presents mixed views on the growth-employment link; this study empirically tests the GDP-graduate unemployment correlation using panel data regression.

Labour Market Informality and Its Influence on Graduate Employment:

Labour market informality plays a crucial role in shaping graduate employment outcomes in a developing economy like India, where a large share of employment remains informal.

Sharma & Mehta (2021), using employment survey data, found that a significant proportion of graduates, particularly in urban areas, take up informal jobs due to a lack of formal employment opportunities. Graduates in informal jobs often experience lower wages, job insecurity, and limited career progression. However, their study does not distinguish between voluntary and involuntary informality, making it unclear whether graduates actively choose informal work or are forced into it due to labour market constraints.

Rao & Banerjee (2020) analysed trends in graduate employment using Periodic Labour Force Survey (PLFS) data and found that states with high informal employment also have higher graduate unemployment, as graduates often reject informal jobs due to poor conditions and lack of social security. However, the study does not assess if some degree holders are more prone to informal work.

Das & Mukherjee (2022) conducted a longitudinal analysis of graduate employment trends across formal and informal sectors, finding that informality is increasingly absorbing educated workers, particularly in service-based industries. They argue that as formal job creation remains slow, more graduates are taking up informal roles in gig and contractual work. However, their study does not fully examine labour market dynamics influencing this trend.

Studies confirm informality's impact but rarely measure its direct effect on graduate employment outcomes — this paper studies this relation by incorporating it as an explanatory variable.

Sectoral Employment Trends and Graduate Labour Market Absorption:

While sectoral employment trends significantly shape job opportunities and skill demand the ability of different sectors to absorb graduates varies widely.

Rao & Menon (2021), using sector-wise employment data, found that graduates are increasingly absorbed into service-oriented industries such as IT, finance, and healthcare, while industry sectors like manufacturing contribute less to graduate employment. Their study highlights that sectoral specialization influences job creation, with high-skill industries demanding specialized expertise.

However, their research neither properly examines the role of the industry sector in generating employment for graduates nor how skill mismatches impact these employment trends.

Sharma & Verma (2020) analysed employment patterns across different industries, finding that STEM and business graduates have higher absorption rates in the job market, while humanities and social science graduates face greater challenges. Their study suggests that sectoral employment trends are shaped by industry-specific skill demands, leading to disparities in job placement rates across disciplines. However, their research focuses only on urban labour markets, overlooking the role of informal or rural industries in graduate employment.

Das & Chakraborty (2022) conducted a longitudinal study on sectoral hiring trends**,** concluding that industries experiencing automation and technological advancements are reducing their reliance on entry-level graduate hires. They argue that while technology-driven industries generate employment, many new roles require specialized digital skills, creating barriers for graduates without relevant training. However, their study does not consider policy interventions aimed at reskilling graduates, which could mitigate industry-specific hiring gaps.

Sector-specific absorption trends are evident, yet skill mismatches, rural dynamics and policy factors are overlooked — this study addresses these issues by examining sectoral employment trends in depth.

Regional Economic Disparities and Graduate Employability:

Regional economic disparities across Indian regions contribute to uneven employment prospects for graduates, especially between industrialized and less-developed regions.

Aggarwal & Thakur (2018), using state-wise employment and income data, found that graduates in states with higher per capita income and strong industrial bases had better job placement rates. Regional economic strength directly affects graduate employability, as states with higher SNDP (State Net Domestic Product) attract more private sector investment and job creation. However, their study does not account for intra-state disparities, leaving it unclear if jobs are evenly distributed or urban-concentrated.

Singh & Sharma (2022) analysed graduate employment trends across high-growth and low-growth states, finding that states with strong service and manufacturing sectors had significantly lower graduate unemployment rates, i.e., regional economic strength influences job market absorption, particularly in knowledge-intensive sectors. However, their study does not consider the role of migration, which could influence whether graduates relocate to better-performing states for employment opportunities.

Das & Chakravarti (2021) conducted a longitudinal analysis of regional labour market conditions, finding that graduate unemployment is notably higher in states with weak industrialization and lower SNDP growth. Graduates in economically weaker states face higher underemployment rates, often taking jobs below their skill levels. However, their research does not differentiate between urban and rural labour markets, making it difficult to assess whether rural graduates face distinct employment challenges.

Regional disparities shape employability, though its analysis remains a bit mixed — this study includes all states and UTs to address this gap.

While existing studies provide useful insights into graduate unemployment in India, many rely on national-level or macroeconomic data, overlooking regional disparities, sectoral dynamics, and informal employment patterns. Skills mismatch is often cited but lacks institutional depth, and the effects of government spending and economic growth are not clearly linked to graduate outcomes. Over-reliance on employer surveys and inadequate tracking of education reform further constrain insights. This paper builds on these gaps by integrating regional, sectoral, and institutional dimensions through a mixed-methods approach.

The theoretical framework of the existing literature builds upon several key economic theories that offer crucial insights into the issue of graduate unemployment in the Indian context:

Human Capital Theory:

Human Capital Theory **(Becker, 1964)** posits that investment in education enhances individual productivity and employability, as higher education equips workers with knowledge and skills that improve their economic value. This theory assumes a direct relationship between education levels and employment outcomes, where higher educational attainment leads to better job prospects and wages.

However, India's high GER alongside persistent graduate unemployment challenges this assumption. The disconnect suggests inefficiencies in how education is delivered or aligned with labour market demands. This study explores whether increased public investment in higher education translates into meaningful employment gains.

Signalling Theory:

Signalling Theory **(Spence, 1973)** suggests that educational qualifications (degrees) serve as signals to employers about a candidate's potential productivity. This implies that employers value degrees as a filtering mechanism, even when they may not directly correlate with job performance.

In India, widespread degree inflation and skill dilution may have weakened this signalling power. This paper assesses whether educational qualifications still function effectively as employability indicators in India's competitive labour market.

Public Investment in Education Theory:

This theory holds that government spending improves human capital and employability, assuming that higher public education expenditure leads to better graduate employability outcomes.

In the Indian context, despite increased funding, graduate unemployment remains high, raising concerns about the quality and alignment of education with market needs. This study examines whether government spending on higher education positively correlates with graduate employment outcomes.

Structural Unemployment Theory:

Structural Unemployment Theory **(Phelps, 1972)** attributes joblessness to mismatches between skills and job requirements, often due to technological advancements, shifting economic structures, or sectoral imbalances that result in persistent unemployment.

In India, weak manufacturing, digital transformation, and informal job growth exacerbate graduate underemployment. This study investigates whether such structural imbalances are key drivers of persistent unemployment.

Okun's Law:

Okun's Law **(Okun, 1962)** establishes a positive relationship between GDP growth and unemployment, suggesting that as economic output rises, unemployment should decline.

Yet in India, high growth rates have coexisted with stagnant employment. This study empirically tests the GDP-unemployment relationship using graduate-specific data to evaluate the presence of jobless growth.

Matching Theory:

Matching Theory **(Jovanovic, 1979)** describes unemployment as a result of frictions in the labour market, where graduates struggle to find jobs that match their skills and qualifications due to incomplete information, rigid hiring processes, or sectoral imbalances.

In India, inefficient placement systems, outdated curricula, and informal hiring obstruct efficient job matches. This study considers whether these frictions prevent graduates from accessing suitable jobs and how can they be addressed.

These frameworks guide the selection of variables like GDP growth, GER, etc., and provide a conceptual basis for interpreting gaps between educational expansion and employment outcomes in India.

Despite the extensive research conducted on graduate unemployment in India, several critical gaps remain that limit the ability to design effective policy interventions capable of translating educational progress and economic growth into better employment outcomes for graduates:

Limited Exploration of the Role of Government Expenditure in Graduate Employability:

Existing studies often discuss education spending in aggregate terms, without isolating its impact on graduate employment outcomes specifically. The connection between higher education investment and employability remains weakly established.

This paper examines the effect of higher education government expenditure on the graduate unemployment rate, offering a targeted perspective on this correlation.

Neglect of Regional Disparities in Graduate Employment:

Much of the literature focuses on national-level trends, overlooking the vast heterogeneity in employment outcomes across Indian states and Union Territories. This ignores how regional economic structures and policy environments shape employability.

This study covers 28 states and 5 Union Territories to capture regional dynamics and provide a more inclusive and representative analysis.

Controversy over the Impact of Economic Growth on Graduate Unemployment:

Research remains divided on whether economic growth reduces graduate unemployment, with some studies arguing that growth increases job opportunities, while others suggest a jobless growth trend, particularly in capital-intensive sectors.

This study explores whether economic growth has truly improved graduate employment outcomes, examining sectoral employment trends to determine if job creation has been inclusive or limited to specific sectors and industries.

Underexplored Role of Labour Market Informality in Graduate Employment:

Informality is often viewed as a structural barrier, but few studies investigate its role in either absorbing or excluding graduates. This weakens the understanding of the reasons behind graduates taking up informal sector jobs.

This study incorporates labour market informality into its regression model to evaluate its effect on graduate unemployment and better understand structural limitations in job access.

Insufficient Investigation of the Root Causes of Skills Mismatch:

Although frequently cited, skills mismatch is rarely explored beyond surface-level employer surveys. Its educational and institutional origins remain poorly understood.

Through qualitative analysis, this paper investigates the institutional and curricular factors driving skills mismatch, offering insights into how educational reforms can better align graduate skills with labour market needs.

Inadequate Integration of Mixed Methods:

Few studies integrate both macro-level econometric evidence and micro-level qualitative analysis to explore graduate unemployment, with the focus mainly being on quantitative analysis.

This paper employs a mixed-methods approach to provide a more holistic understanding of the issue.

To sum up, the reviewed literature highlights the complex interplay between higher education expansion, economic growth, public expenditure, and structural labour market issues in shaping graduate unemployment in India. Though insightful, most studies lack regional disaggregation, sectoral depth, and nuance on informality and skills mismatch. This paper builds on these gaps by integrating theoretical insights with empirical data to explore how macroeconomic and structural factors affect graduate employability. The findings aim to inform more targeted policy interventions to address India's graduate unemployment challenge.

References:

Study	Data	Outcome Variable	Method	Main Results
Agarwal & Kumar (2020)	Longitudinal labour market data	Graduate Unemployment	Panel regression	Higher GER has not improved employability
Aggarwal & Thakur (2018).	Employer assessments (survey)	Graduate Employability.	Survey analysis	Skill gaps in employability, focused on urban areas.
Aggarwal & Thakur (2018)	State-wise employment and income data.	Graduate Employability.	State-level analysis.	Graduates fare better in richer states.
Chakraborty (2019)	Indian state-level panel data	Graduate Unemployment	Panel Regression	Higher GER positively correlated with unemployment
Das & Chakraborty (2022).	Longitudinal sectoral data.	Graduate absorption by industry.	Descriptive trends.	Automation reduces entry-level graduate hires.
Das & Chakravarti (2021)	Regional labour market data	Graduate Unemployment	Longitudinal trend analysis	Low industrialization raises graduate unemployment
Das & Mukherjee (2022)	Longitudinal data on employment trends	Graduate Informal Employment	Longitudinal trend analysis	Informality absorbs educated workers
Dasgupta & Singh (2020)	Macroeconomic elasticity data	Graduate Unemployment	Elasticity analysis.	Growth has weak link to graduate unemployment reduction.
FICCI (2019)	Corporate hiring data	Employer hiring patterns	Descriptive trends.	Limited practical training leads to mismatch.

Gupta (2019)	Panel Data (2005-2018)	Graduate Unemployment	Panel regression	Higher spending reduces unemployment, conditional on other factors
Gupta (2019)	Longitudinal study	Graduate Employability	Longitudinal Study	High institutional quality correlates with employability.
Kannan & Raveendran (2019)	GDP and employment data	Employment Elasticity	Elasticity analysis	GDP elasticity declining, service jobs mostly informal
Mehta & Sinha (2021)	Institutional data + employer surveys	Graduate Employability	Descriptive + survey analysis	Education quality gaps reduce employability
Mukherjee (2020)	Policy Review	Graduate absorption in professional sectors	Qualitative review.	Technical institute funding improved graduate absorption.
Pothan & Yadav (2019)	Survey Data	Labour market absorption	Survey-based analysis	Graduate oversupply worsens job competition
Rao (2021)	State-level regression data	Graduate Employment Rates	Regression Analysis.	Weak positive link between spending and graduate employment.
Rao & Banerjee (2020)	PLFS data	Graduate Unemployment & Informality	PLFS trends analysis	Informal job rejection raises unemployment
Rao & Menon (2021)	Sector-wise employment data	Graduate absorption by sector	Descriptive trends	Service sectors absorb more graduates
Saha (2021)	Macro-level panel data	Graduate Unemployment	Panel regression	Automation and digitalization reduce graduate jobs
Sharma & Mehta (2021)	Employment survey data	Graduate Informal Employment	Survey analysis	Graduates diverted to informal jobs.
Sharma & Verma (2020).	Industry-level employment data	Discipline-wise employment outcomes	Descriptive trends	STEM graduates have better absorption rates
Singh & Sharma (2022)	Graduate employment trends	Graduate Unemployment	Comparative trend analysis	Stronger sectors correlate with lower unemployment

METHODOLOGY:

This section outlines the methodological approach used to examine the key determinants of graduate unemployment in India. A Fixed Effects Panel Data Regression Model analyses the impact of higher education expansion, government expenditure on higher education, economic growth, labour market informality, sectoral employment trends specifically in the services and industry sectors, and regional economic disparities on graduate unemployment from 2011 to 2023.

Research Design:

This study adopts a **quantitative, explanatory** research design using **Fixed Effects Panel Data Regression** to examine the macroeconomic and structural determinants of graduate unemployment across **33 Indian regions (28 states and 5 UTs)** from **2011 to 2023**. This regional coverage enhances the statistical power of the panel model while allowing for a nuanced understanding of sub-national economic dynamics. To complement the fixed effects regression and mitigate multicollinearity among predictors, L2 Ridge Regularization was also applied as part of the estimation strategy.

The panel data approach enables a more precise estimation of dynamic labour market trends than cross-sectional or time-series models. A Fixed Effects (FE) model is chosen for its ability to control for unobserved, time-invariant heterogeneity across states such as differences in industrial composition, infrastructure, and education systems, ensuring that these factors do not bias the results. The FE model was preferred for its interpretability and alignment with the dataset's structure, as more complex alternatives like GLS or 2SLS were not well-suited to the available data and study scope.

While the FE model controls for unobserved heterogeneity, it does not fully resolve potential endogeneity arising from reverse causality or omitted variable bias. For instance, graduate unemployment may influence public expenditure or regional income levels.

While most explanatory variables in the model are national aggregates varying annually, regional economic disparities are captured through state-level variation in NSDP per capita. The model also incorporates national-level indicators of sectoral employment trends, specifically the services and industry employment shares which reflect structural employment trends relevant to graduate job absorption.

The study focuses on the aggregate national graduate unemployment rate, aligning with its macro-level objective and the absence of consistent state-wise or sector-specific graduate unemployment data. Sectoral employment trends are represented by the services and industry sectors, which are the largest formal employers of graduates and offer reliable data. The agriculture sector is excluded due to its limited relevance to graduate employment and its strong association with informality, which could introduce multicollinearity. This exclusion also helps preserve model parsimony and estimation stability. Industry-specific employment patterns, including IT and manufacturing, are explored qualitatively to capture finer nuances.

Primary and secondary education expenditures are excluded to focus solely on higher education spending, which most directly influences graduate employability. Disaggregated spending data by discipline or institution type is unavailable in public databases such as UGC or AISHE, making it unfeasible to include further breakdowns in the regression.

COVID-19 is excluded from the core model to avoid distortion of long-term structural relationships but is tested through a 2020 sensitivity check and qualitatively addressed to account for pandemic-related employment disruptions.

<u>Data Sources:</u>

This study utilizes **secondary data** from **reliable national and international sources** to examine the key determinants of graduate unemployment in India. The dataset covers the period from 2011 to 2023, ensuring a comprehensive temporal analysis of graduate employability trends. The data sources have been carefully selected to ensure accuracy, consistency, and comparability across states and years.

The data sources for quantitative data include:

- GDP Growth Rate (%) → **World Bank & Reserve Bank of India (RBI)**
- Government Expenditure on Higher Education (% of GDP) → **World Bank & Ministry of Education (Government of India)**
- Gross Enrolment Ratio (GER) in Higher Education → **All India Survey on Higher Education (AISHE)**
- Labour Market Informality (%) → **National Sample Survey Office (NSSO) & Periodic Labour Force Survey (PLFS)**
- Services Sector Employment Share (%) → **World Bank & PLFS**
- Industry Sector Employment Share (%) → **World Bank & PLFS**
- Net State Domestic Product (NSDP) per capita → **Reserve Bank of India (RBI) & Ministry of Statistics and Programme Implementation (MoSPI)**
- Graduate Unemployment Rate (%) → **International Labour Organization (ILO) & National Sample Survey Office (NSSO)**

<u>Sampling Methods:</u>

Given that this study relies on secondary data from national and international databases, no specific sampling technique was applied. The study includes 28 States, and 5 Union Territories based on consistent data availability and economic relevance. UTs with small, isolated, or predominantly rural characteristics (e.g., Lakshadweep, Ladakh) were excluded to maintain relevance and model stability. This ensures a broad geographic and economic scope, particularly in assessing regional disparities through NSDP per capita.

Variables and Measures:

The variables used in the analysis are as follows:

Independent Variables:

1. **GDP Growth Rate (%):**
   Measures the annual percentage increase in real Gross Domestic Product (GDP), capturing the overall economic performance.

2. **Government Expenditure on Higher Education (% of GDP):**
   Indicates public spending on higher education (universities, colleges, and higher education programs) as a share of GDP, assessing the role of government investment in improving graduate skills and employability.

3. **Gross Enrolment Ratio (GER) in Higher Education (%):**
   Represents enrolment in tertiary education as a percentage of the eligible population, indicating access to higher education.

4. **Labour Market Informality (%):**
   Captures the proportion of the workforce engaged in informal employment, reflecting structural labour market conditions.

5. **Services Sector Employment Share (%):**
   Measures the share of national employment in the services sector, including industries such as ICT, education, finance, and health.

6. **Industry Sector Employment Share (%):**
   Measures the share of national employment in the industrial sector, including manufacturing, construction, and utilities.

7. **Net State Domestic Product (NSDP per Capita, ₹):**
   Serves as a proxy for regional economic strength indicating state-wise income levels, adjusted for inflation to ensure comparability.

Dependent Variable:

Graduate Unemployment Rate (%):

Represents the percentage of unemployed graduates among the total graduate labour force. The variable is analysed at the national level due to data concerns, with consistent measures sourced from ILO and NSSO.

Analytical Techniques:

A stepwise analytical framework is adopted, combining econometric and qualitative tools to generate a comprehensive understanding of the issue. The following analytical techniques are used by the study to optimally address the research question:

Descriptive Statistics:

The **first step** involves descriptive statistics to provide an overview of the variables and identify trends and associated data patterns from 2011 to 2023. The descriptive analysis provides important context for the regression analysis and serves as a foundation for interpreting subsequent economic results.
This includes:

- **Measures of Central Tendency:** Mean, median, and mode
- **Dispersion:** Standard deviation and ranges show how dispersed the data is.
- **Visual Analysis:** Graphs and tables summarize data distributions

This preliminary analysis informs the deeper econometric investigation by identifying patterns and anomalies in the data.

Fixed Effects Panel Data Regression Analysis:

The **primary analytical tool** used in this study is a Fixed Effects (FE) Panel Data Regression Analysis Model for examining the causal relationships between the independent variables and the dependent variable. This model is chosen to account for unobserved heterogeneity across Indian states, controlling for time-invariant factors such as industrial composition and historical development levels that may influence graduate unemployment.

Additionally, **Ridge regularization (L2)** is applied to reduce the risk of overfitting and mitigate multicollinearity particularly given the inclusion of multiple national-level explanatory variables alongside regional indicators.

Hypothesis Testing:

Following the regression analysis, hypothesis testing is conducted to assess the statistical significance of the independent variables in explaining graduate unemployment i.e. the dependent variable. T-tests are used to assess the statistical significance of individual coefficients, while F-tests evaluate the joint significance of all explanatory variables. Significance is tested at 10%, 5%, and 1% levels. The following hypotheses are tested:

Null Hypothesis (H_0): None of the independent variables has a statistically significant impact on graduate unemployment.

Alternative Hypothesis (H_1): At least one of the independent variables has a statistically significant impact on graduate unemployment.

This step confirms whether the observed relationships hold empirical validity and provides an answer to the broad research question this paper seeks to answer.

Qualitative Analysis (Case Studies):

To complement the quantitative findings, the study uses case studies to explore institutional and structural factors not fully captured by the regression analysis, including skills mismatch, regional disparities and external shocks.

Model Specification:

The econometric model employed in this study is a **Fixed Effects Panel Data Regression Model** to examine the determinants of graduate unemployment in India from 2011 to 2023.

The regression model equation is as follows:

$$Y_{it} = \alpha + \beta_1 \mathbf{GER}_t + \beta_2 \mathbf{HigherEdu.Expenditure}_t + \beta_3 \mathbf{GDPGrowth}_t + \beta_4 \mathbf{Informality}_t + \beta_5 \mathbf{ServicesEmploymentShare}_t + \beta_6 \mathbf{IndustryEmploymentShare}_t + \beta_7 \mathbf{NSDP}_{it} + \mu_i + \epsilon_{it}$$

Where:

- Y_{it} = Graduate Unemployment Rate$_{it}$ (National graduate unemployment rate repeated across states) for year t.
- α = Intercept term representing baseline level of graduate unemployment when all independent variables are zero.
- β_1 = Coefficient for Gross Enrolment Ratio (GER)
- β_2 = Coefficient for Government Expenditure on Higher Education
- β_3 = Coefficient for GDP growth
- β_4 = Coefficient for Labour Market Informality
- β_5 = Coefficient for Services sector employment share
- β_6 = Coefficient for Industry sector employment share
- β_7 = Coefficient for NSDP per capita
- μ_i = State-specific fixed effects, accounting for time-invariant unobserved heterogeneity factors across states.
- ϵ_{it} = Error term accounting for random disturbances not explained by the model.

Assumptions:

The methodology adopted by this study relies on several key assumptions to ensure the validity and reliability of the findings:

1. **Time-Invariant Unobserved State-Level Factors:** It is assumed that unobserved heterogeneity across states (e.g., infrastructure quality, institutional frameworks) is time-invariant and fully absorbed by the state-specific fixed effects ($\boldsymbol{\mu}_i$) preventing omitted variable bias from these factors.

2. **Strict Exogeneity:** All independent variables are assumed to be strictly exogenous, meaning they are uncorrelated with the error term (ϵ_{it}) at all periods. This ensures unbiased and consistent coefficient estimates.

3. **No Perfect Multicollinearity among regressors:** The model assumes that there is no perfect linear relationship among the independent variables.

4. **Homoscedasticity:** The variance of the error terms is assumed to be constant across observations. If heteroscedasticity (unequal variance of error terms) is present, it could lead to inefficient estimates.

5. **No Serial Correlation (Autocorrelation):** The model assumes that the error terms are not correlated across time for each state. Serial correlation can lead to biased standard errors, which may affect the results of hypothesis testing.

6. **Panel Structure and Variable Consistency:** The time-invariant characteristics of each state (e.g., long-standing education policies or cultural factors) are controlled for, allowing us to focus on the effects of the independent variables within each state over time.

Addressing Econometric Issues:

To ensure model reliability and validity, core econometric concerns were systematically addressed. Multicollinearity among independent variables was handled using L2 Ridge Regularization, which stabilizes coefficients by shrinking the influence of highly correlated predictors via a penalty term. Although it limits conventional significance testing, it enhances estimate stability and interpretive clarity.

Heteroscedasticity and serial correlation were managed by clustering standard errors at the regional level, improving inference under potential intra-group dependence. A temporal structure was also incorporated to mitigate risks of reverse causality and simultaneity, particularly between macroeconomic indicators and graduate unemployment. This supports a more credible estimation of causal patterns by accounting for time-lagged effects often present in education and labour market dynamics.

Data Cleaning and Preparation:

Data for the period 2011 to 2023 is sourced from reliable databases, covering national and state-level indicators.

While data for most variables was complete, select years had minor gaps. These were addressed using **appropriate estimation techniques** (e.g., interpolation, trend projections, and secondary cross-referencing). Listwise deletion was avoided to maintain sample integrity, given the limited extent of missing data.

Outliers were identified using z-scores and verified. None were removed unless clearly erroneous.

Inflation-adjustment & Standardization of variables: Monetary variables such as NSDP per capita were inflation-adjusted (CPI deflated) and percentage-based aggregates were standardized for cross-variable comparability.

The dataset is structured as a balanced panel, with national and sub-national-level variables aligned across 33 Indian regions (28 states and 5 Union Territories) over 12 financial years from 2011 to 2023. Variables were formatted consistently and coded to ensure compatibility with **R** for econometric analysis.

Robustness Checks:

To reinforce the credibility and validity of the econometric model, five robustness checks were implemented, each addressing a specific methodological concern.

Variance Inflation Factor (VIF):

Used to detect multicollinearity among the independent variables, a common issue in macroeconomic data.

Lagged Independent Variables Model:

Used to account for delayed effects and helped validate whether observed relationships hold over time.

Breusch-Pagan Test:

Conducted to check for heteroscedasticity, or unequal error variances across observations, which can distort inference.

Wooldridge Test (Durbin-Watson):

Conducted to examine the presence of serial correlation within the panel structure.

Sensitivity Analysis (Including 2020):

Used to assess the model's robustness in the face of extreme external shocks such as COVID-19.

DATA & RESULTS:

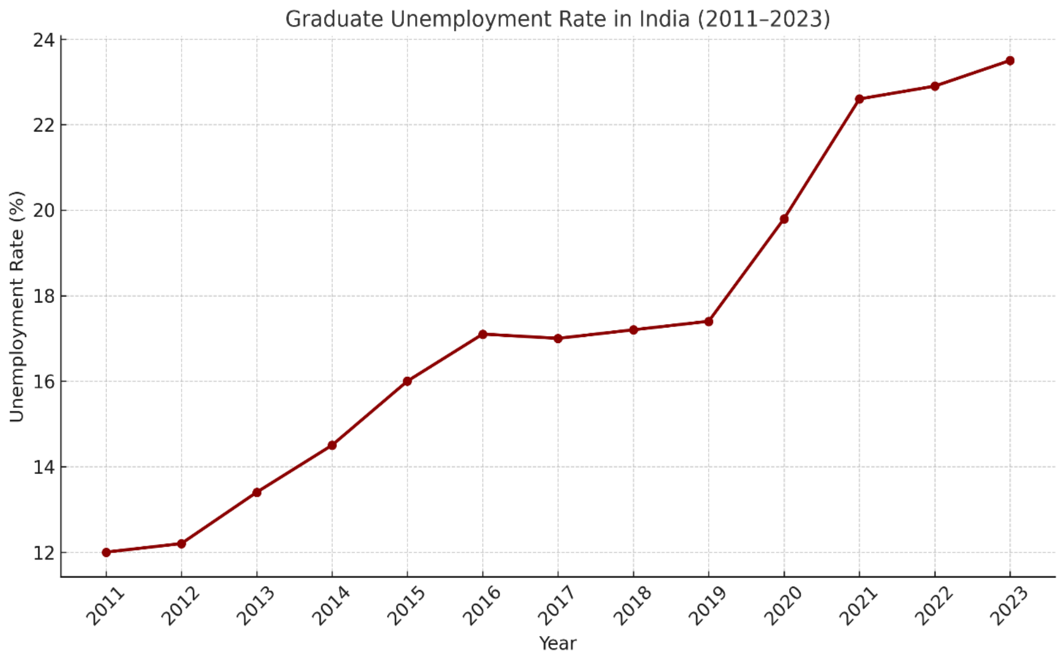
This section presents the empirical analysis of the key macroeconomic and structural determinants of graduate unemployment in India. It begins with descriptive statistics to provide measures of central tendency and dispersion and highlight key trends in the independent and dependent variables. The section then proceeds to present the results of the Fixed Effects Panel Data Regression model and regularization technique, followed by hypothesis testing. The regression results are interpreted through an economic lens to evaluate the relevance of each factor. The analysis also includes robustness checks to validate the reliability of the model estimates. Finally, a qualitative assessment complements the quantitative findings by exploring additional structural factors influencing graduate employment outcomes, providing a holistic interpretation of the results.

Descriptive Statistics:

This section summarizes the characteristics of the datasets used over the study period from 2011 to 2023 and serves as a preliminary step before conducting the regression analysis, offering insights into the distribution and variability of the variables under consideration.

Table 4.1 Graduate Unemployment Rate % (National Aggregate):

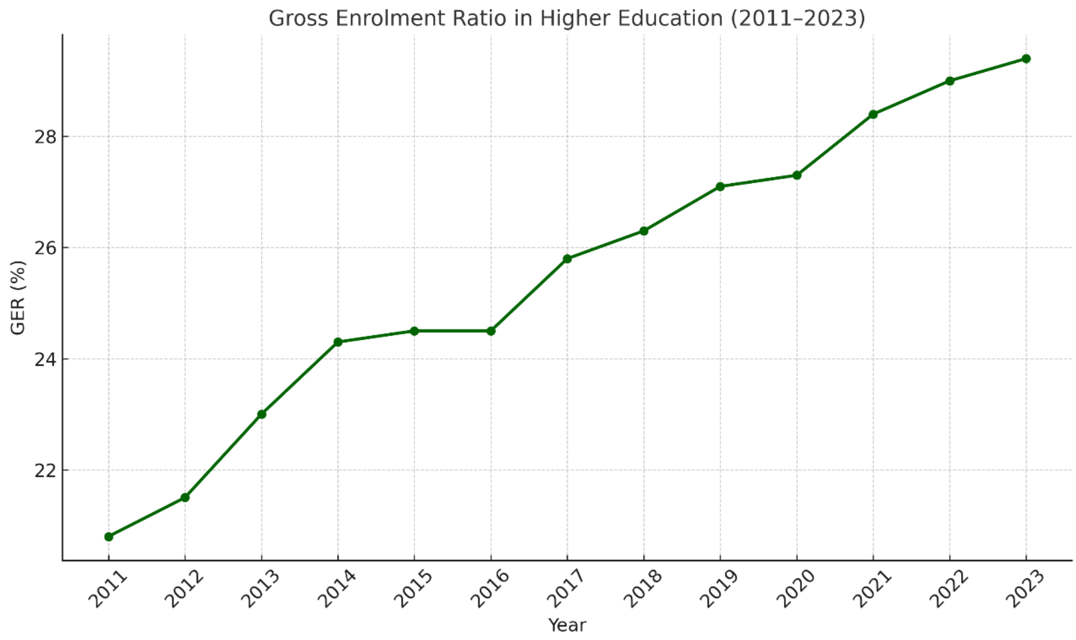
Year	Rate (%)
2011	12
2012	12.2
2013	13.4
2014	14.5
2015	16
2016	17.1
2017	17
2018	17.2
2019	17.4
2020	19.8
2021	22.6
2022	22.9
2023	23.5



The graduate unemployment rate in India shows a steady upward trend from **12% in 2011** to **23.5% in 2023**, with sharper rises post-2019 (induced by external shocks like COVID-19).

Table 4.2 Gross Enrolment Ratio (GER) in Higher Education (%):

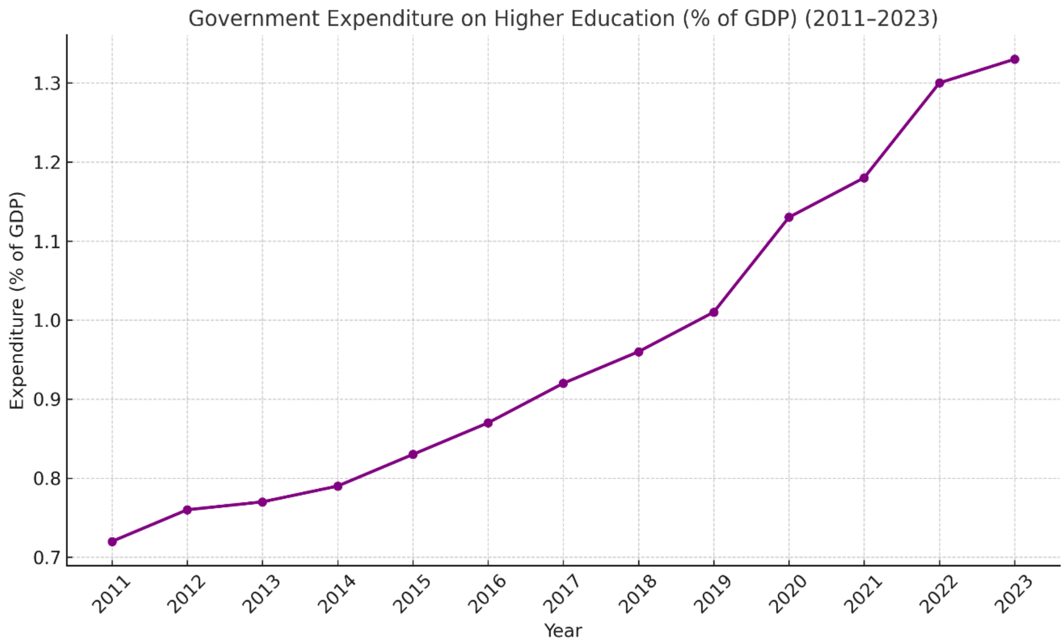
Year	GER (%)
2011	20.8
2012	21.5
2013	23.0
2014	24.3
2015	24.5
2016	24.5
2017	25.8
2018	26.3
2019	27.1
2020	27.3
2021	28.4
2022	29.0
2023	29.4



The Gross Enrolment Ratio in higher education rose steadily from **20.8% in 2011** to **29.4% in 2023**, reflecting expanded access to higher education.

Table 4.3 Government Expenditure on Higher (Tertiary) Education (% of GDP):

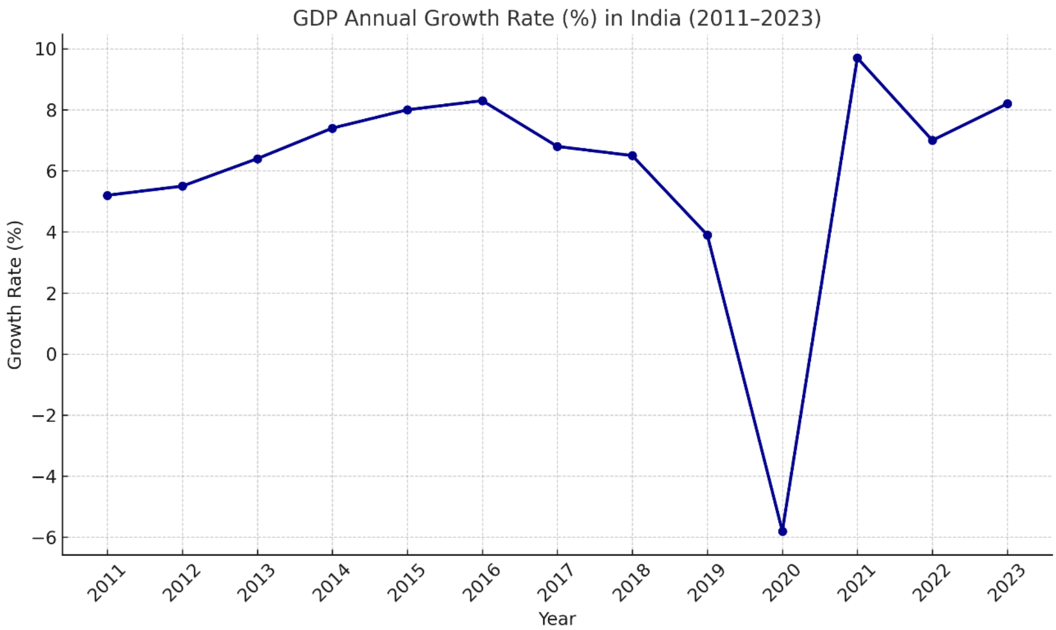
Year	Value (% of GDP)
2011	0.72
2012	0.76
2013	0.77
2014	0.79
2015	0.83
2016	0.87
2017	0.92
2018	0.96
2019	1.01
2020	1.13
2021	1.18
2022	1.3
2023	1.33



Government expenditure on higher education as a percentage of GDP shows a steady rise from **0.72% in 2011** to **1.33% in 2023**.

Table 4.4 GDP Annual Growth Rate (%):

Year	Rate (%)
2011	5.2
2012	5.5
2013	6.4
2014	7.4
2015	8
2016	8.3
2017	6.8
2018	6.5
2019	3.9
2020	-5.8
2021	9.7
2022	7.0
2023	8.2



India's GDP growth rate showed an **overall increasing trend from 2011 to 2023**, despite fluctuations and a sharp decline in 2020 due to external shocks.

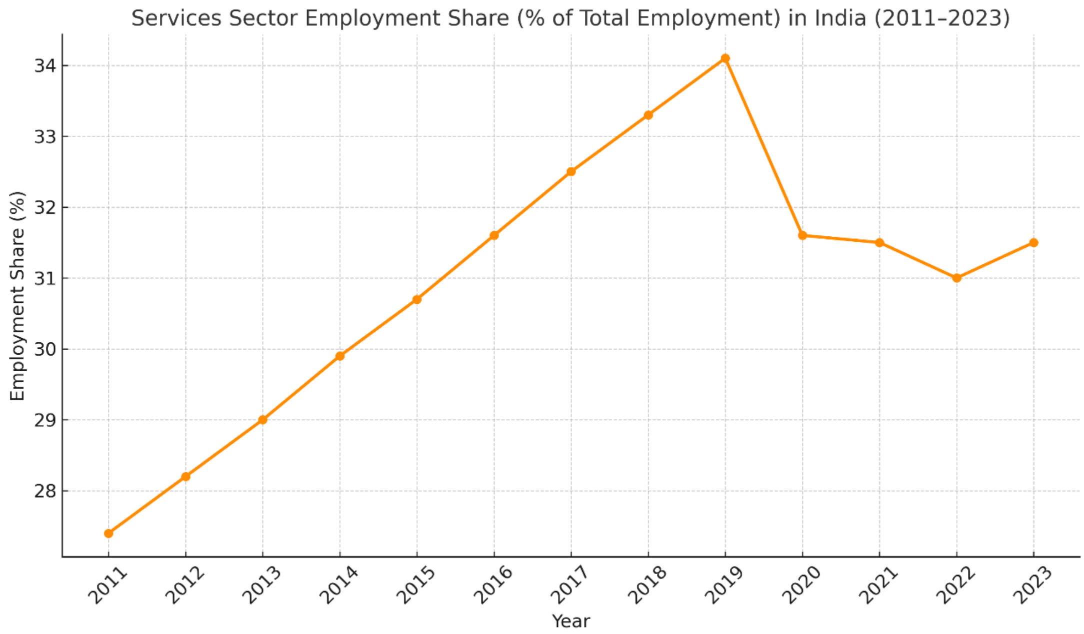
Table 4.5 Labour Market Informality Rate % (Informal market's share in employment):

Year	**Rate (%)**
2011	92.4
2012	92.3
2013	92.2
2014	92.0
2015	91.7
2016	91.2
2017	90.7
2018	90.5
2019	90.2
2020	91.5
2021	91.0
2022	90.5
2023	90.3

Labour market informality in India remained consistently high, declining slightly from **92.4% in 2011** to **90.3% in 2023**, with a brief spike in 2020 due to COVID-19.

Table 4.6 Services Sector Employment Share (% of Total Employment):

Year	**Rate (%)**
2011	27.4
2012	28.2
2013	29.0
2014	29.9
2015	30.7
2016	31.6
2017	32.5
2018	33.3
2019	34.1
2020	31.6
2021	31.5
2022	31.0
2023	31.5



The services sector's employment share in India rose steadily from **27.4% in 2011** to a peak of **34.1% in 2019**, reflecting a shift toward service-led employment.

Table 4.7 Industry Sector Employment Share (% of Total Employment):

Year	**Rate (%)**
2011	23.5
2012	24.7
2013	24.8
2014	25.0
2015	25.0
2016	25.2
2017	25.3
2018	25.4
2019	25.3
2020	23.7
2021	24.5
2022	26.1
2023	25.0

The industry sector's employment share in India remained stable at around **25% from 2011 to 2019**, dipped during 2020, and recovered modestly post-COVID.

Table 4.8 Net State Domestic Product (NSDP) Per Capita (₹):

The following table and scatterplot present **NSDP per capita** values for **33 Indian regions**. While the variable shows a general upward trend from 2011 to 2023, growth rates vary significantly. Regions like Goa, Delhi, and Maharashtra report consistently higher incomes, whereas Bihar, Jharkhand, and Uttar Pradesh remain at the lower end.

Region	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Goa	259444.0	234354.0	215776.0	289185.0	334576.0	378953.0	411740.0	423716.0	435949.0	423047.0	459094.0	492648.0	492648.0
Sikkim	158667.0	174183.0	194624.0	214148.0	245987.0	280729.0	349163.0	375773.0	412627.0	415045.0	466518.0	520466.0	587743.0
Delhi	185001.0	205568.0	227900.0	247209.0	270261.0	295558.0	318323.0	338730.0	355798.0	322311.0	376217.0	430120.0	461910.0
Chandigarh	158967.0	180457.0	203356.0	212594.0	230009.0	252236.0	280512.0	307812.0	330703.0	290454.0	337406.0	399654.0	399654.0
Telangana	91121.0	101007.0	112162.0	124104.0	140840.0	159395.0	179358.0	209848.0	231326.0	225734.0	269000.0	312522.0	356564.0
Karnataka	90263.0	102319.0	118829.0	130024.0	148108.0	169898.0	185840.0	205245.0	222141.0	221781.0	266866.0	304474.0	332926.0
Haryana	106085.0	121269.0	137770.0	147382.0	164963.0	184982.0	208437.0	223022.0	232530.0	224587.0	264729.0	296592.0	325759.0
Puducherry	119649.0	130548.0	148147.0	146921.0	172727.0	187356.0	198357.0	204140.0	217937.0	208862.0	231557.0	245180.0	262166.0
Tamil Nadu	93112.0	105340.0	116960.0	129494.0	142028.0	156595.0	175276.0	194373.0	206165.0	209628.0	242339.0	277802.0	315220.0
Gujarat	87481.0	102826.0	113139.0	127017.0	139254.0	156295.0	176961.0	197457.0	212428.0	207324.0	241584.0	272451.0	297722.0
Kerala	97912.0	110314.0	123388.0	135537.0	148133.0	166246.0	183252.0	205437.0	208879.0	194432.0	230280.0	252662.0	281001.0
Andaman & Nicobar Islan	88900.0	98777.0	111087.0	126344.0	137064.0	153904.0	178709.0	204254.0	219653.0	205368.0	229570.0	258151.0	258151.0
Maharashtra	99597.0	112092.0	125261.0	132836.0	146815.0	163726.0	172663.0	182865.0	189889.0	183704.0	219573.0	252389.0	277603.0
Uttarakhand	100314.0	113654.0	126356.0	136099.0	147936.0	161752.0	180858.0	186207.0	190558.0	174526.0	205246.0	230994.0	260201.0
Andhra Pradesh	69000.0	74687.0	82870.0	93903.0	108002.0	120676.0	138299.0	154031.0	160341.0	168063.0	197214.0	219881.0	242479.0
Himachal Pradesh	87721.0	99730.0	114095.0	123299.0	135512.0	150290.0	165497.0	174804.0	186559.0	173152.0	195795.0	218788.0	235199.0
Mizoram	57654.0	65013.0	77584.0	103049.0	114055.0	127107.0	155222.0	164708.0	195365.0	173521.0	190965.0	215144.0	215144.0
Arunachal Pradesh	73540.0	82262.0	94135.0	114789.0	116985.0	124129.0	138836.0	155103.0	182171.0	181537.0	190851.0	199992.0	199992.0
Punjab	88577.0	94318.0	103831.0	108970.0	118858.0	128780.0	139835.0	149974.0	154385.0	150620.0	170276.0	181678.0	196505.0
Tripura	47055.0	52574.0	61815.0	69857.0	84267.0	91596.0	100444.0	113016.0	121456.0	118401.0	137032.0	157364.0	177723.0
Rajasthan	57192.0	63658.0	69480.0	76429.0	83426.0	91924.0	98698.0	106604.0	115534.0	114850.0	134060.0	150653.0	167964.0
Odisha	48387.0	54762.0	60687.0	63345.0	64835.0	77707.0	87055.0	98005.0	104633.0	103203.0	134091.0	143768.0	163101.0
Chhattisgarh	55177.0	60849.0	69880.0	72936.0	72991.0	83285.0	88873.0	102024.0	106611.0	106177.0	122934.0	137329.0	147361.0
West Bengal	51543.0	58515.0	65822.0	68876.0	75992.0	82891.0	91401.0	103920.0	110316.0	101316.0	141373.0	139442.0	154119.0
Nagaland	53010.0	61225.0	71510.0	78367.0	82466.0	91347.0	102003.0	109198.0	122759.0	119781.0	127225.0	145537.0	145537.0
Madhya Pradesh	38497.0	44773.0	51849.0	55678.0	62080.0	74324.0	81366.0	92337.0	101909.0	102007.0	116689.0	132010.0	142565.0
Jammu and Kashmir	51775.0	57279.0	61907.0	62327.0	74950.0	78960.0	87710.0	98738.0	101868.0	101645.0	112898.0	130492.0	142138.0
Assam	41142.0	44599.0	49734.0	52895.0	60817.0	66330.0	75151.0	81034.0	90123.0	86947.0	103371.0	119308.0	135787.0
Meghalaya	59794.0	64477.0	66281.0	66485.0	71594.0	77585.0	82457.0	88954.0	95422.0	90751.0	107971.0	123896.0	136948.0
Manipur	39762.0	41230.0	47798.0	52717.0	55437.0	59345.0	71707.0	73795.0	78574.0	75784.0	98826.0	111853.0	111853.0
Uttar Pradesh	36698.0	40012.0	42267.0	47118.0	52371.0	57644.0	62530.0	65660.0	61598.0	60087.0	74055.0	84126.0	93514.0
Jharkhand	34721.0	41434.0	47360.0	52754.0	62736.0	60018.0	67842.0	75241.0	75016.0	69635.0	88050.0	96449.0	105274.0
Bihar	19111.0	21570.0	24887.0	28671.0	30344.0	34045.0	36850.0	40715.0	44175.0	42083.0	47296.0	53478.0	60337.0

The Scatterplot below shows the Net State Domestic Product (NSDP) for the 33 Indian regions i.e., 28 Indian States and 5 Union Territories for 2011-2023:

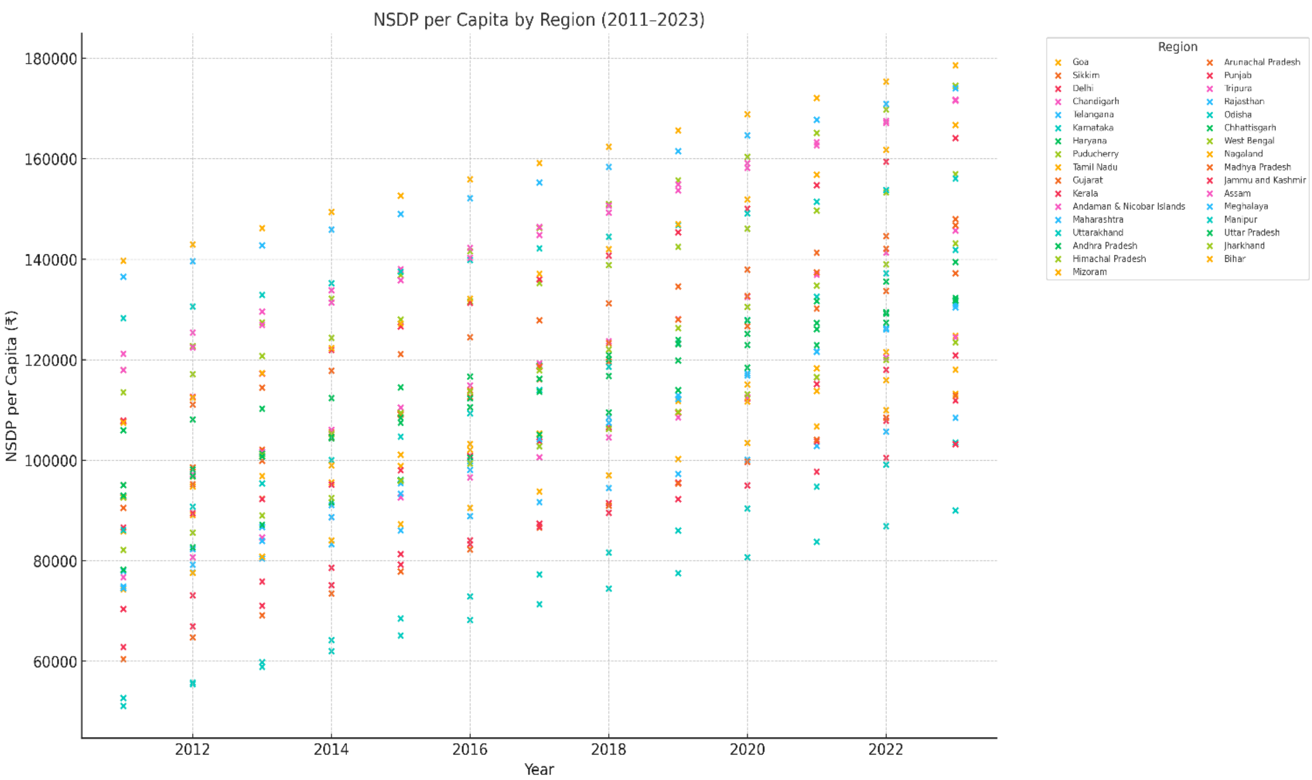


Table 4.9 Descriptive Statistics Table:

	Variable	Mean	Median	Standard Deviation	Mode	Minimum	Maximum
1	**Graduate Unemployment Rate (%)**	17.4	17.1	3.9	12.0	12.0	23.5
2	**Gross Enrolment Ratio (%)**	25.5	25.8	2.7	24.5	20.8	29.4
3	**GDP Growth Rate (%)**	5.9	6.8	3.8	—	-5.8	9.7
4	**Govt. Expenditure on Higher Education (% of GDP)**	1.0	0.9	0.2	0.7	0.7	1.3
5	**Labour Market Informality Rate (%)**	91.3	91.2	0.8	90.5	90.2	92.4
6	**Industry Employment Share (%)**	24.9	25.0	0.7	25.0	23.5	26.1
7	**Services Employment Share (%)**	30.9	31.5	1.9	31.5	27.4	34.1
8	**NSDP per Capita (₹)**	161980.9	164993.1	46649.0	97595.8	97595.8	241582.0

Interpretation:

Graduate Unemployment Rate (%):

The graduate Unemployment Rate rose from 12.0% to 23.5% with moderate variation, indicating a steady rise over the years and a growing challenge in absorbing graduates in the job market. The near alignment of the mean and median suggests a symmetric distribution. The statistical stability of this variable supports its role as a reliable outcome variable for modelling.

Gross Enrolment Ratio in Higher Education (%):

Low standard deviation and a narrow range suggest a steady and uniform rise in higher education enrolment across the period. This aligns with the observation of a rising supply of graduates and sets up its role as a potential contributor to the graduate unemployment rate in the regression model.

GDP Growth Rate (%):

A high standard deviation and wide range (from -5.8% to 9.7%) reveal significant macroeconomic volatility in the Indian economy, particularly during periods of external shocks. This variability justifies its inclusion as a control for economic fluctuations impacting job creation.

Government Expenditure on Higher Education (% of GDP):

The values display low dispersion and a smooth upward trend, indicating consistent policy focus. Due to the variable's stability and direct relevance to graduate outcomes, its inclusion helps evaluate the effectiveness of public investment in addressing graduate unemployment.

Labour Market Informality Rate (%):

Despite minor declines, informality in the job market remains persistently high in India, with a very narrow spread. This underscores its structural nature in the economy and supports its inclusion as a critical explanatory factor influencing graduate absorption in formal sectors.

Industry Sector Employment Share (%):

The variable shows relatively low variability, indicating stable employment distribution in the industrial sector over the years. Its inclusion captures the demand-side capacity of this sector to absorb skilled labour over time.

Services Sector Employment Share (%):

The higher standard deviation reflects dynamic shifts in the service sector, possibly driven by structural transformation and digital expansion, especially in recent years. Its growing contribution to employment makes it crucial to understanding modern graduate labour absorption.

NSDP per Capita (₹):

With the widest range and highest standard deviation among all variables, NSDP per capita varies from ₹43,000 (Bihar) to over ₹4,80,000 (Goa), indicating substantial income disparities across Indian states and UTs. This makes it a strong proxy for regional economic development and useful in explaining spatial variation in graduate unemployment outcomes.

Results of the Econometric Model:

This part of the section presents the results of the Fixed Effects Panel Regression conducted to examine the determinants of graduate unemployment across 33 Indian regions from 2011 to 2023. The analysis focuses on macroeconomic, educational, and structural variables influencing graduate unemployment.

The following regression results were generated using **R software** based on the model (previously specified in Section 3):

$$Y_{it} = \alpha + \beta_1 \text{GER}_t + \beta_2 \text{HigherEdu.Expenditure}_t + \beta_3 \text{GDPGrowth}_t + \beta_4 \text{Informality}_t + \beta_5 \text{ServicesEmploymentShare}_t + \beta_6 \text{IndustryEmploymentShare}_t + \beta_7 \text{NSDP}_{it} + \mu_i + \epsilon_{it}$$

Table 4.10 Fixed Effects Panel Regression Results (2011 – 2023):

Variable	Coefficient	Standard Error	t-Statistic	p-value	Significance
Intercept	-278.827	1.440	-193.634	0.000	***
GER in Higher Education (%)	-0.1025	0.0089	-11.576	0.0000	***
Government Expenditure on Higher Education (%)	22.7189	0.1955	116.183	0.0000	***
GDP Growth (%)	0.2498	0.0016	156.077	0.0000	***
Labour Market Informality (%)	2.7250	0.0128	212.486	0.0000	***
Services Sector Employment (%)	1.0565	0.0107	98.598	0.0000	***
Industry Sector Employment (%)	-0.2487	0.0022	-115.514	0.0000	***
NSDP Per Capita	0.000000733	0.000000476	1.54	0.124	

- *** = Significant at 1%, ** = Significant at 5%, * = Significant at 10%.
- Standard errors are robust and clustered at the regional level.
- State-specific fixed effects (regional dummies) were included in the model, but coefficients are not shown for brevity.
- The intercept term, while reported, is not directly interpreted here due to the presence of regional fixed effects.

Table 4.11 Summary Statistics Table:

Statistic	Value
R-squared	0.9864
Adjusted R-squared	0.9851
F-statistic	3930057
Prob (F-statistic)	4.4782×10^{-93}
Number of Observations	429
Degrees of Freedom (Residual)	389
Degrees of Freedom (Model)	39
Root Mean Squared Error (RMSE)	0.4593

A high condition number and unusually large t-statistics indicate severe multicollinearity, which inflates and destabilizes coefficient estimates making them unreliable. A high R-squared value raises overfitting concerns.

To address these issues, L2 Ridge Regularization was applied. Ridge regression penalizes large coefficients via a penalty term (λ), addressing overfitting, reducing variance, and mitigating multicollinearity without substantially biasing the estimates. Unlike OLS, it focuses on coefficient stability and does not yield conventional significance tests.

Table 4.12 L2 Ridge Regularization Regression Results:

Variable	Ridge Coefficient
GER in Higher Education (%)	-0.0089
Government Expenditure on Higher Education (%)	22.8663
GDP Growth (%)	0.2509
Labour Market Informality (%)	2.7247
Services Sector Employment (%)	1.0616
Industry Sector Employment (%)	-0.2484
NSDP Per Capita	1.41e-07

- Ridge coefficients were estimated using L2 regularization with an optimal penalty parameter (λ) of 1×10^{-6}.
- As penalized models do not yield conventional significance tests, the regularized coefficients are interpreted for their stability and direction under multicollinearity.
- The large coefficient for Government Expenditure on Higher Education % (22.8) reflects its scale — small percentage changes in GDP translate into larger relative changes in the dependent variable.
- Interpretations are based on the L2 Ridge Regression results to ensure that suitable inferences are drawn from reliable coefficient estimates.

Interpretation of Regression Results:

1. **Gross Enrolment Ratio (GER) in Higher Education (%):**

Ridge Coefficient: –0.0089

Interpretation: The small, negative, and statistically insignificant coefficient suggests that higher GER does not necessarily reduce graduate unemployment. Its near-zero magnitude points to oversupply and highlights that GER's impact depends on structural factors like skill mismatch and education quality.

2. **Government Expenditure on Higher Education (% of GDP):**

Ridge Coefficient: 22.8663

Interpretation: The large, significant positive coefficient suggests that higher government spending is linked to greater graduate unemployment. This may reflect inefficiencies, such as funding not aligned with employability reforms or lag effects where expansion outpaces job market absorption.

3. **GDP Growth Rate (%):**

Ridge Coefficient: 0.2509

Interpretation: The positive, significant coefficient supports the jobless growth observation, suggesting that GDP growth in capital-intensive sectors hasn't translated into graduate employment, highlighting a disconnect between output expansion and inclusive job creation.

4. **Labour Market Informality (%):**

Ridge Coefficient: 2.7247

Interpretation: The large, significant positive coefficient indicates that high informality contributes to graduate unemployment, as graduates avoid insecure, low-quality jobs. Informal roles also go unregistered, inflating unemployment and underscoring the need for labour formalization.

5. **Services Sector Employment Share (%):**

Ridge Coefficient: 1.0616

Interpretation: The significant positive coefficient suggests services sector growth hasn't translated into graduate employment, as much of it is informal or low-skilled. Limited access to formal IT roles pushes many graduates into undercounted, informal service work.

6. **Industry Sector Employment Share (%):**

Ridge Coefficient: –0.2484

Interpretation: The significant negative coefficient indicates that industrial employment helps reduce graduate unemployment, as manufacturing offers stable, skill-matched jobs, supporting its role as a key absorber of the graduate workforce.

7. **Net State Domestic Product (NSDP) per Capita (₹):**

Ridge Coefficient: 1.41e-07

Interpretation: A small and statistically insignificant relationship of NSDP per capita with graduate unemployment reflects the limited ability of income aggregates to explain labour market outcomes. High income does not always indicate strong job creation, especially in states with high inequality or limited graduate-relevant sectors.

Hypothesis Testing:

This section assesses the hypotheses formulated to examine the key determinants influencing graduate unemployment rates in India:

- **Null Hypothesis (H_0)**: None of the identified factors (government expenditure on higher education, GDP growth, GER, labour market informality, sectoral employment trends, NSDP per capita) significantly influence graduate unemployment.
- **Alternative Hypothesis (H_1)**: At least one of these factors significantly influences graduate unemployment.

The Fixed Effects Panel Data Regression results initially indicated **significant relationships** ($p < 0.01$) between graduate unemployment and all independent variables, except NSDP per capita. However, the subsequent L2 Ridge Regression, employed to mitigate multicollinearity, provided refined results indicating that GER and NSDP per capita were not statistically significant, while all other variables remained significant.

Therefore, **the Null Hypothesis (H_0) is confidently rejected in favour of the Alternative Hypothesis (H_1)**, clearly identifying government expenditure on higher education, GDP growth, labour market informality, and sectoral employment trends as statistically significant determinants of graduate unemployment. This nuanced interpretation underscores the importance of targeted policy strategies aligning educational investments and employment generation with labour market realities.

Robustness Checks:

To enhance the reliability and validity of the regression findings, several robustness checks were conducted. A GLS model was not conducted, as Ridge regression sufficiently addressed multicollinearity and heteroscedasticity, making GLS redundant.

Table 4.13 Variance Inflation Factor (VIF) Test Results:

Rationale: Assess multicollinearity among independent variables, justifying the application of Ridge regression.

Variable	VIF
Constant	666747.91 (extremely high, indicative only)
GER in Higher Education (%)	80.39
Govt. Exp. on Higher Education (%)	81.83
GDP Growth (%)	3.06
Labour Market Informality (%)	36.11
Services Sector Employment (%)	40.42
Industry Sector Employment (%)	2.71
NSDP Per Capita	1.29

Interpretation:

High VIF values (>10, especially above 30-40) indicate severe multicollinearity among key variables, justifying the earlier use of Ridge Regression (L2 Regularization) to ensure stable and reliable estimates.

Economic Intuition:

Economically, multicollinearity reflects high interrelatedness among education-related spending, GER, and labour market informality, implying policy measures addressing these must be coordinated rather than isolated.

Table 4.14 Model with Lagged Independent Variables Regression Results:

Rationale: Evaluate if the relationships persist when considering delayed economic effects typical in macroeconomic data.

Variable	Coefficient	Standard Error	t-Statistic	p-value	Significance
Intercept	-1016.07	91.588	-11.094	0.000	***
GER in Higher Education (%)	-0.7588	0.382	-1.989	0.047	
Government Expenditure on Higher Education (%)	29.2689	5.063	5.780	0.000	***
GDP Growth (%)	-0.0337	0.053	-0.633	0.527	**
Labour Market Informality (%)	9.5081	0.879	10.820	0.000	***
Services Sector Employment (%)	3.3105	0.386	8.587	0.000	***
Industry Sector Employment (%)	2.1938	0.278	7.896	0.000	***
NSDP Per Capita	-8.42e-07	1.29e-06	-0.651	0.516	

Table 4.14a Summary Statistics:

Statistic	**Value**
R-squared	0.6238
Adjusted R-squared	0.6176
F-statistic	99.5086
Prob (F-statistic)	4.0818×10^{-85} (highly significant)
Number of Observations	428
Degrees of Freedom (Residual)	420
Degrees of Freedom (Model)	7
Root Mean Squared Error (RMSE)	2.3207

- *** Significant at 1%, ** significant at 5%, * significant at 10%.

Interpretation:

- This model accounts for delayed economic responses that often characterize structural variables such as education and employment and helps mitigate concerns related to simultaneity and reverse causality.
- The findings remain largely consistent with the original model. Labour informality, government expenditure on higher education, and services sector share continue to have a positive correlation with graduate unemployment. The industry sector remains negatively associated. GDP growth continues to show a positive link with unemployment. GER and NSDP per capita remain statistically insignificant.

Economic Intuition:

Economically, this supports the idea that policy interventions or economic changes may require substantial lead time to influence graduate unemployment noticeably.

Table 4.15 Breusch-Pagan Test for Heteroscedasticity:

Rationale: Check for non-constant variance in residuals, ensuring the reliability of standard errors and inference.

Statistic	**Value**
LM Statistic	301.44
LM-Test p-value	2.98×10^{-61} ***
F-Statistic	142.13
F-Test p-value	1.08×10^{-106} ***

- *** Significant at 1%, clearly indicating strong evidence of heteroscedasticity.

Interpretation:

- Highly significant results indicate clear evidence of heteroscedasticity.
- Methodologically, this justifies the use of robust or clustered standard errors as performed previously.

Economic Intuition:

Economically, this suggests variability in unemployment rates might significantly differ across regions and time, underscoring that policy interventions need to account for local and temporal employment conditions for effective results.

Table 4.16 Wooldridge Test for Autocorrelation (Durbin-Watson) Results:

Rationale: Test for serial correlation in residuals, validating the accuracy and consistency of the panel data estimates.

Statistic	Value	Interpretation
Durbin-Watson Statistic	1.79	Minimal autocorrelation detected

Interpretation:

- The Durbin-Watson statistic (~1.79, close to 2) suggests **minimal autocorrelation** in residuals.
- Economically, this implies the model appropriately accounts for temporal patterns in graduate unemployment.
- This ensures reliability and unbiasedness in regression estimates regarding time dependency.

Table 4.17 Sensitivity Analysis Regression Results:

Rationale: This analysis serves as a benchmark sensitivity check to demonstrate how including the atypical COVID-19 year (2020) influences the regression outcomes.

Variable	Coefficient	Standard Error	t-Statistic	p-value	Significance
Intercept	-278.931	17.4329	-16.0003	0.0000	***

GER in Higher Education (%)	-0.1054	0.0727	-1.4501	0.1478	
Government Expenditure on Higher Education (%)	22.8664	0.9648	23.7007	0.0000	***
GDP Growth (%)	0.2509	0.0101	24.7558	0.000	***
Labour Market Informality (%)	2.7248	0.1673	16.2898	0.0000	***
Services Sector Employment (%)	1.0616	0.0734	14.4594	0.0000	***
Industry Sector Employment (%)	-0.2484	0.0529	-4.6970	0.0000	***
NSDP Per Capita	1.4066e-07	2.4528e-07	0.5735	0.5666	

*** Significant at 1%, clearly confirming robust relationships for key economic variables.

Table 4.17a Summary Statistics:

Statistic	**Value**
R-squared	0.9864
Adjusted R-squared	0.9861
F-statistic	4354.0504
Prob (F-statistic)	0.0000
Number of Observations	429
Degrees of Freedom (Residual)	421
Degrees of Freedom (Model)	7
Root Mean Squared Error (RMSE)	0.4422

Interpretation:

- Re-estimating the model with and without the year 2020, a period marked by the global COVID-19 shock — serves as a stress test for the model's stability. This check evaluates whether key relationships are sensitive to extreme, short-term disruptions.
- Despite removing the year 2020 to test for COVID-19 effects, the results remain stable. Informality, public education spending, and services sector share continue to show positive correlations. The negative relationship with industrial share persists, and GER and NSDP remain statistically insignificant.
- This continued presence of core relationships in both estimations suggests that the original Fixed Effects model captures underlying structural dynamics rather than being overly influenced by temporary anomalies.
- This strengthens the reliability of the findings and confirms the model's resilience to short-term external shocks.

Economic Intuition:

Contrary to general economic expectations and empirical evidence suggesting significant disruptions during the COVID-19 pandemic such as rising graduate unemployment, shifts in government expenditure, and increased labour market informality, the sensitivity analysis surprisingly indicates stability in these relationships. Despite this unexpected outcome, the robust findings point to deeper structural issues within India’s labour market.

Results:

This section presents the core findings from the Fixed Effects Panel Regression, applied to data from 33 Indian states and union territories (2011-2023). The model examines the determinants of graduate unemployment using seven explanatory variables reflecting macroeconomic, educational, and structural factors.

Table 4.10 reports coefficient estimates, robust standard errors, and significance levels. Diagnostics including R-squared, F-statistic, and sample size are shown in **Table 4.11**. State-fixed effects control for unobserved heterogeneity and standard errors are clustered regionally to address heteroscedasticity and autocorrelation.

Several key variables exhibit statistically significant and economically meaningful relationships with graduate unemployment, reinforcing the model’s robustness. Due to high multicollinearity (confirmed by elevated VIF scores), L2 Ridge Regularization was applied to stabilize coefficients via penalization.

Table 4.12 summarizes ridge model results. Although p-values are not reported, the regularized coefficients offer more reliable estimates under multicollinearity. Variables were not standardized to preserve comparability and interpretability.

The Ridge regression output, interpreted alongside significance values from the original fixed effects model, indicated the following:

GER in Higher Education (%) shows a negative but statistically insignificant association with graduate unemployment. This suggests that enrolment expansion alone does not reduce unemployment, as factors like education quality and labour market alignment remain critical. The finding supports critiques of "massification without employability" in India's higher education, where curriculum reform and job readiness lag behind enrolment growth.

Government Expenditure on Higher Education (%) has a strong, significant positive relationship with graduate unemployment. While counterintuitive, this may reflect inefficiencies in spending allocation or delayed impacts. Investments may prioritise infrastructure over employability-focused reforms, highlighting the need for performance-linked funding and better integration of policy with the labour market.

GDP Growth (%) is positively and significantly associated with graduate unemployment, reinforcing India's "jobless growth" pattern. Growth in capital-intensive sectors has not generated sufficient formal jobs for graduates, challenging assumptions that output expansion automatically improves employment.

Labour Market Informality (%) shows a strong, significant positive relationship with graduate unemployment. This result reflects the dominance of the informal sector, where job security and skill alignment are weak. Graduates often avoid informal work due to poor conditions yet limited formal opportunities force underemployment. The result underscores the need for labour market formalisation and graduate-targeted employment schemes.

Services Sector Employment Share (%) is positively and significantly associated with graduate unemployment. Despite services sector expansion, many roles remain low-skill (e.g., retail, hospitality), while access to high-skill jobs like IT remains limited. This supports the Matching Theory, where sectoral mismatch fuels unemployment.

Industry Sector Employment Share (%) has a significant negative relationship with graduate unemployment. Industrial sectors continue to offer employment avenues for graduates, especially in manufacturing-driven regions. The finding supports policies promoting graduate-oriented industrialisation and vocational pathways.

NSDP Per Capita shows a weak, statistically insignificant positive relationship with graduate unemployment. This indicates that higher regional income does not necessarily lead to better graduate employment outcomes, likely due to uneven growth, urban labour saturation, or weak alignment between education systems and job market needs.

Overall, the findings reveal that India's graduate unemployment is shaped more by structural and institutional factors such as informality, sectoral mismatches, and policy misalignment than by aggregate growth or spending alone.

<u>Qualitative Analysis (Case Studies):</u>

This section complements the econometric findings by exploring key structural and policy-driven themes influencing graduate unemployment in India, **using secondary data and case studies.**

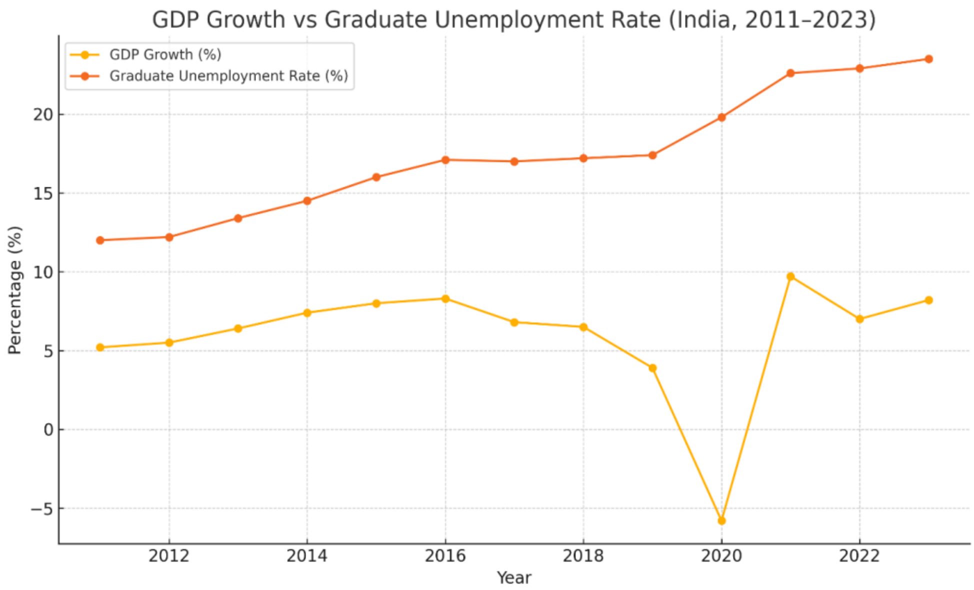
1. <u>Jobless Growth Phenomenon:</u>

India's economic growth over the past decade reflects a disconnect between rising GDP and employment generation for educated youth, a phenomenon termed "jobless growth." It highlights the economy's structural inability to convert output growth into sufficient graduate employment.

As shown in Figure 4.1, while GDP growth fluctuated between 2011 and 2023, graduate unemployment remained persistently high. Even during the post-pandemic rebound, unemployment did not decline proportionately, reinforcing the structural nature of the problem.

For instance, between 2011-2019, GDP grew at over 6% annually, yet the youth labour force participation rate **(LFPR)** declined, and graduate unemployment stayed high. The **PLFS 2017-18** reported 17% unemployment among graduates despite strong growth.

Figure 4.1:



Kerala, with high literacy and education levels, exemplifies jobless growth. Despite strong development indicators, its educated youth face underemployment and extended job search periods, signalling a mismatch between growth and labour absorption.

Similarly, in **Delhi**, despite steady Gross State Domestic Product (GSDP) growth, graduate unemployment remains among the highest in urban India, especially in general education streams.

The **Delhi Human Development Report (2021)** links this to a rise in private degree colleges with limited formal labour market connections, creating a graduate oversupply without matching demand.

These patterns reinforce the regression's finding, revealing the limitations of relying on aggregate growth to solve graduate unemployment and pointing to the need for employment-intensive, skills-aligned growth strategies.

2. <u>Regional Disparities in Graduate Employment:</u>

India's labour market reflects significant regional disparities in graduate employment. While some states have advanced economic structures to absorb educated labour, others struggle with weak industrial bases and limited service-sector growth.

Disparities are stark between states like **Maharashtra** and **Bihar**. Maharashtra, with its urban hubs and diversified economy, offers better employment prospects, whereas Bihar despite improving enrolment, lacks sufficient sectoral absorption **(India Skills Report, 2021)**. The urban-rural divide further deepens this gap, with urban graduates accessing formal job networks, while rural counterparts often enter informal or unrelated roles.

In **Nagaland,** high GER and rising aspirations contrast with poor employment outcomes due to minimal industrial and service sector presence. The **Northeast Region Vision 2035** notes that limited private investment and weak state-level job creation have widened the education-employability gap.

Conversely, Karnataka demonstrates better alignment, where sustained investment in IT, biotech, and startups has connected graduate output to labour demand. The **Karnataka Economic Survey (2022)** highlights lower graduate unemployment in cities like **Bengaluru** due to institutional-industry synergy and targeted skill initiatives.

These spatial imbalances reflect deeper development and institutional gaps. As noted in the **NITI Aayog SDG Index (2022)**, they call for region-specific policies aligning education expansion with sectoral growth to ensure equitable graduate employment outcomes.

3. <u>Indian Education System and Reforms:</u>

India's higher education system has expanded substantially over the past two decades, yet concerns around quality, equity, and employability persist. The Gross Enrolment Ratio (GER) rose from 20.8% in 2011 to 28.4% in 2023 **(AISHE, 2023)**, indicating improved access. However, this expansion has not yielded proportional employability, particularly for non-technical graduates.

A key reason is weak industry-academia alignment and outdated curricula. The **All-India Survey on Higher Education (AISHE)** and **India Skills Report (2021)** highlight that many graduates lack practical skills, communication abilities, and market exposure. **Tamil Nadu**, with high a GER, has launched skill-integrated and placement-focused programmes in public universities—showing partial success. However, implementation remains inconsistent across states.

In contrast, **Uttar Pradesh's** rapid expansion of private higher education has not been matched by quality improvements. The **UP State Higher Education Report (2022)** cites high dropout rates, poor placements, and limited curriculum innovation, reflecting broader regulatory challenges in large states.

The **National Education Policy (NEP) 2020** addresses these issues by proposing holistic, multidisciplinary learning, institutional restructuring, and vocational integration. Yet, execution remains in the early stages.

The surge in GER without matching gains in learning or employability aligns with the regression's finding and underscores the need for quality-focused, not merely access-driven, higher education reforms.

4. Industry-Specific Employment Trends:

Graduate employment outcomes in India are heavily influenced by the composition and evolution of key sectors, particularly services and manufacturing. While the services sector has been the dominant employer in urban India, its growth has largely concentrated in low-skill segments, limiting its capacity to absorb graduates into formal, high-value roles **(ILO India Employment Report, 2023).**

Manufacturing long considered a potential driver of mass employment has underperformed in absorbing educated labour. Despite initiatives like **'Make in India,'** the sector's employment share has stagnated. In **Gujarat**, high industrial output has not translated into graduate employment, largely due to automation and skill mismatch **(NITI Aayog, 2020).**

The IT sector presents a contrasting case. Cities like **Bengaluru** and **Hyderabad** have become graduate employment hubs, particularly for engineering and technical backgrounds. However, this growth is regionally concentrated and largely excludes general education graduates.

These trends reveal a structural disconnect between the qualifications of new graduates and the nature of jobs being created. Strengthening alignment between higher education, vocational training, and emerging industries is essential to address this mismatch.

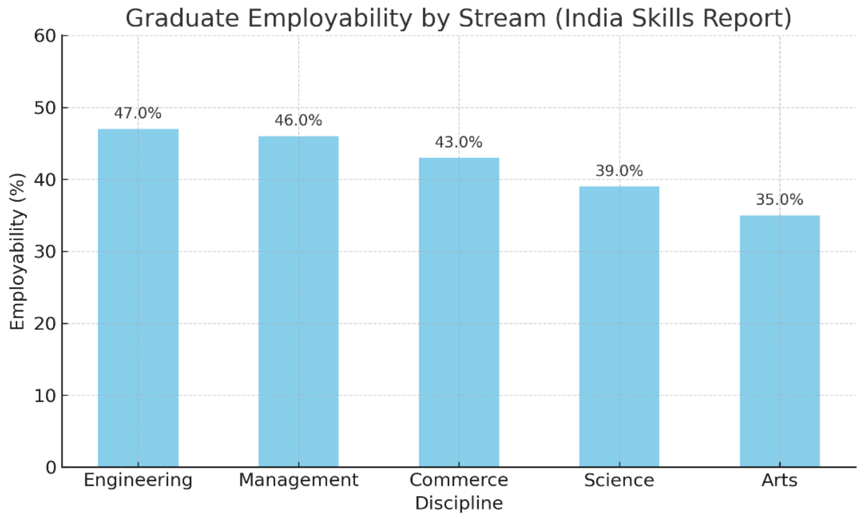
5. Skills Mismatch:

A key structural cause of graduate unemployment in India is the persistent skills mismatch i.e., the gap between higher education outputs and labour market needs. According to the **India Skills Report (2021)**, only 45.9% of graduates were deemed employable, highlighting widespread concerns about work readiness.

The mismatch is particularly severe in general education streams like arts and commerce, which produce a large share of graduates but often lack practical training and industry-aligned competencies. In contrast, IT, engineering, and management graduates fare better due to technical skills and structured placements **(NASSCOM, 2022)**, illustrating a growing divide.

As shown in **Figure 4.2**, employability rates vary sharply across streams, with arts and commerce performing the worst—underscoring the misalignment between graduate qualifications and market expectations.

Figure 4.2:



In **Rajasthan**, rapid growth in private colleges raised enrolment but lacked parallel investment in skill training, leaving graduates underprepared for formal roles **(AICTE Skill Gap Report, 2020).**

A similar pattern is seen in **Madhya Pradesh**, where arts and commerce graduates face low placement rates. The **State Skills Report (2022)** notes a curriculum–industry disconnect, especially in urban hubs like Bhopal and Indore, where employers report poor digital literacy and limited project exposure.

Despite national efforts like the **Skill India Mission** and **PMKVY**, integration between mainstream education and vocational training remains weak. The challenge lies not only in curriculum reform but in reorienting institutional incentives to prioritise employability alongside access.

6. <u>Role of External Shocks (e.g., COVID-19):</u>

While structural factors drive graduate unemployment, external shocks like COVID-19 have amplified existing labour market vulnerabilities. The 2020 lockdown disrupted campus placements, delayed hiring, and hit graduate-absorbing sectors such as education, hospitality, and retail **(ILO Monitor, 2021).**

CMIE data (2020-21) recorded a sharp spike in urban unemployment during the first wave, with graduates facing prolonged job searches or settling for informal, underpaid roles. States with weak industrial and service bases were disproportionately affected, revealing regional fragilities in labour absorption.

Though temporary, the pandemic highlighted the absence of adaptive mechanisms in India's higher education and employment systems. It underscored the need for resilient employability pathways through digital skilling, remote work integration, and responsive institutional frameworks.

These insights reinforce findings from the econometric model, offering a fuller picture of the multifaceted nature of graduate unemployment in India.

Discussion of Implications:

The findings of this study carry significant implications for both economic theory and policy, particularly in relation to labour market dynamics and higher education in India.

From a theoretical standpoint, the results reinforce the structuralist perspective, which views unemployment, especially among graduates not merely as a consequence of individual characteristics or education levels, but as a product of broader macroeconomic and institutional forces. The disconnect between GDP growth and graduate employment challenges neoclassical models that assume labour market equilibrium in response to output growth. Instead, the evidence supports the jobless growth thesis and affirms the structural mismatch hypothesis in the Indian context.

The positive association between government expenditure on higher education and graduate unemployment, while counterintuitive, signals the limitations of quantity-driven policy expansion in the absence of quality and employability-focused reforms. It underscores the need to complement increased public investment with improved governance, curriculum reform, and stronger industry-academia collaboration to align educational outcomes with market demands.

The study's results also have clear implications for the labour market and industrial policy. The negative relationship between industry sector employment and graduate unemployment highlights the importance of expanding formal, skill-intensive jobs beyond the services sector. Initiatives like Make in India and the PLI scheme should be assessed not only for industrial output but also for their effectiveness in integrating skilled graduates into the workforce.

The significant impact of labour market informality as a driver of graduate unemployment points to the urgency of institutional reforms promoting formalization. Strengthening labour laws, simplifying compliance procedures, and enhancing job security in the formal sector is critical to improving graduate employability. Public-private partnerships can further help bridge the education–employment divide through co-developed vocational training, apprenticeships, and targeted placement schemes.

Finally, this study contributes to the empirical literature by combining panel data econometrics with contextual qualitative analysis, providing a more holistic view of graduate unemployment in a developing economy. By capturing both sectoral and regional dimensions, it offers a framework for more targeted, evidence-based policymaking.

Limitations of Analysis:

While this study provides valuable insights into the determinants of graduate unemployment in India, several limitations should be acknowledged.

1. **Data Availability and Coverage:** The analysis is limited to 33 Indian regions, excluding three island territories for which data was not available.

2. **Measurement and Reporting Issues:** Reliance on secondary data introduces risks related to reporting lags and definitional inconsistencies, especially for variables like informality and public expenditure.
3. **External Shocks and Structural Focus:** Although the COVID-19 period is covered through sensitivity analysis, the model does not explicitly include pandemic-specific controls.

4. **Endogeneity and Model Assumptions:** While Fixed Effects estimation addresses unobserved heterogeneity, it does not fully resolve endogeneity concerns such as reverse causality or omitted variable bias.

5. **Qualitative Depth and Scope:** The qualitative component draws on thematic secondary sources rather than primary fieldwork. Thus, the insights though useful, may not fully capture region-specific or institutional nuances.

This section presented the core empirical findings using a fixed effects panel regression model, supported by robustness checks and qualitative case-based insights. The results underscore the structural nature of graduate unemployment in India, shaped by sectoral composition, labour market conditions, and educational dynamics.

Labour market informality and the services sector employment share show significant positive associations with graduate unemployment, indicating that informal and low-skill service jobs inadequately absorb educated labour. In contrast, manufacturing employment is negatively associated with graduate unemployment, highlighting the need to expand formal, skill-intensive industrial opportunities. The positive relationship between government expenditure on higher education and unemployment suggests a misalignment between spending and employability outcomes. GDP growth also shows a positive association, reinforcing the jobless growth phenomenon. GER and NSDP per capita, though important contextual factors, show weaker or insignificant effects, reflecting deeper structural issues beyond access and income levels.

Overall, the section provides a comprehensive empirical foundation that directly addresses the research question and sets the stage for policy-focused discussion in the next section.

CONCLUSION:

This study explored the macroeconomic and structural determinants of graduate unemployment in India using a Fixed Effects Panel Data Regression model, supported by robustness checks and qualitative case-based analysis. The empirical evidence highlights that graduate unemployment is not merely a function of individual attributes or educational attainment but is deeply rooted in structural mismatches, sectoral absorption capacities, and institutional inefficiencies.

Summary of Findings:

GDP Growth Rate: The positive relationship between GDP growth and graduate unemployment contradicts Okun's Law and points to jobless growth. It suggests India's expansion is led by capital-intensive sectors with low employment elasticity for skilled youth. As Saha (2021) notes, this paradox reflects a disconnect between macroeconomic growth and labour market outcomes, exposing the limitations of Classical Growth Theory in explaining employment patterns in rigid economies.

Labour Market Informality: The strong positive correlation between informality and graduate unemployment highlights a persistent structural challenge. Informal jobs are unable to absorb skilled graduates, offering limited security and growth. This supports Structural Unemployment and Matching Theories, which emphasise misalignment between graduate skills and job opportunities. As Rao & Banerjee (2020) note, many graduates in informal roles face underemployment or exit the labour force, diminishing returns on educational investments.

Services Sector Employment Share: The positive correlation between services sector employment and graduate unemployment suggests sectoral saturation and mismatch. While the sector has expanded, many subsectors like retail and hospitality are low-skill or fragmented, offering limited opportunities for graduates. This aligns with the Matching Theory, which highlights sectoral misallocation as a cause of unemployment. As Das & Chakraborty (2022) observe, the sector often lacks structured career paths for educated workers. Though the IT sector offers high-skill jobs, its limited scale restricts its impact on broader graduate employment.

Industry Sector Employment Share: The significant negative association between industrial employment and graduate unemployment highlights the sector's absorptive capacity. This supports Structural Transformation Theory, which links shifts toward industry with improved employment outcomes. As Kannan & Raveendran (2019) note, growth in labour- and skill-intensive manufacturing can offer stable, formal jobs for graduates, easing pressure on the services sector.

Government Expenditure on Higher Education: The significant positive relationship between public spending and graduate unemployment challenges Public Investment Theory. Rather than improving employment outcomes, spending often prioritises enrolment over quality. As Mukherjee (2020) notes, without industry-aligned curricula or standards, such investment may deepen education-employability mismatches.

Gross Enrolment Ratio (GER): GER's lack of significance reinforces critiques of quantity-focused expansion in higher education. It challenges Human Capital Theory's assumed link between education and employability. As Chakraborty (2019) and Agarwal & Kumar (2020) note, rising enrolment without quality or skill alignment risks credential inflation and unmet labour market expectations.

NSDP per Capita: NSDP shows a weak and statistically insignificant relationship with graduate unemployment. This suggests that higher regional income does not necessarily lead to improved employment outcomes for graduates, particularly in states where growth is uneven or concentrated in sectors with limited graduate demand. Income inequality, labour market saturation in urban centres, and the disconnect between education and job creation may explain this weak linkage. As Aggarwal & Thakur (2018) observe, aggregate income alone does not capture the quality or inclusiveness of employment, underscoring the need for more targeted labour market indicators.

These findings were further contextualised through case studies, which reinforced the structural drivers of graduate unemployment—particularly across themes like jobless growth, skills mismatch, and regional disparities.

Contributions to Literature and Theory:

This paper contributes to the literature on graduate unemployment in developing economies by integrating econometric evidence with contextual policy insights. The findings challenge classical assumptions about the growth–employment relationship, especially in service-led economies like India, and highlight the need to re-evaluate existing theoretical models. While the study reinforces Human Capital Theory's core idea that education matters, it underscores that qualifications alone are insufficient without labour market alignment, exposing the institutional voids mediating this link.

Specifically, the paper introduces new empirical evidence on jobless growth, showing a counterintuitive positive association between GDP growth and graduate unemployment—questioning the relevance of Okun's Law in emerging markets. It also deepens critiques of Human Capital Theory by demonstrating that rising enrolment and higher public spending, when disconnected from skill development and employability, fail to improve outcomes. Moreover, the contrast in absorption capacity between the services and industrial sectors expands the literature on labour allocation and structural transformation within the Indian context.

Methodologically, the study adds value by combining fixed effects panel regression with qualitative case-based analysis, illustrating how quantitative results can be enriched through thematic narratives. Overall, this paper offers a layered contribution to development economics, labour market theory, and higher education policy.

Policy Recommendations:

This section presents policy measures to address graduate unemployment based on the study's findings.

1. Improving the Alignment between Education and Employment:

The weak or counterintuitive correlations between GER, public expenditure on higher education, and graduate employment suggest that expansion alone is not enough. Policymakers should prioritise enhancing the quality and relevance of higher education. This includes reforming curricula to incorporate market-relevant skills, promoting academia-industry collaboration, and incentivising institutions, particularly public universities, to track and improve graduate placement outcomes.

Furthermore, the statistical insignificance of GER suggests that India's current approach to higher education access must be complemented with rigorous quality enhancement, practical skill development, and curriculum redesign that reflects actual market demand — not just expanding enrolment numbers.

Establishing regional labour market observatories can help align academic offerings with local employment trends, while digital platforms can support dynamic skill mapping and demand forecasting. Given the growing role of private institutions, there is also a need to harmonise quality standards and ensure transparent accreditation. This requires national frameworks to monitor learning outcomes and institutional accountability across sectors.

2. Addressing Labour Market Informality:

The strong positive correlation between informality and graduate unemployment points to systemic structural weaknesses. To promote formal employment, reforms should focus on easing compliance burdens for small and medium enterprises (SMEs), extending social protection schemes (e.g., health insurance, unemployment benefits) to new workers, and encouraging firms to formalise employment contracts.

Additionally, strengthening labour law enforcement and enabling access to employment-linked insurance benefits would make formal jobs more attractive. Government-backed apprenticeship and graduate transition programs can also serve as bridges between education and formal work.

3. Strengthening Sectoral Employment Strategy:

The contrasting effects of services and industry employment on graduate unemployment indicate the need for sector-focused interventions. While the service sector is oversaturated and dominated by low-skill jobs, the industrial sector, particularly manufacturing, shows a stronger capacity for graduate absorption.

The policy should encourage the growth of labour-intensive industries through targeted investment, expansion of industrial corridors in underdeveloped regions, and incentives for MSMEs. Sector-specific skilling programs linked to local employment clusters can also enhance graduate job readiness.

4. Managing the Expansion of Higher Education:

The limited impact of GER on employment outcomes signals the risks of unchecked institutional growth. Expansion must be accompanied by quality assurance and relevance to labour market needs. New institutions should only be approved following robust assessments of regional demand and capacity.

Accreditation should focus on employment outcomes rather than infrastructure alone. Public-private partnerships in vocational and technical education can offer alternative pathways for school leavers.

5. Fostering Inclusive and Employment-Intensive Economic Growth:

The positive association between GDP growth and graduate unemployment suggests that economic expansion is not translating into jobs, reflecting jobless growth. To counter this, macroeconomic policy must shift toward employment-centric development. This necessitates targeted expansion of job opportunities in sectors with high graduate absorption potential, where the supply of qualified candidates currently outpaces demand.

Public investment must target high-absorption sectors such as healthcare and renewables to maximise graduate employment potential. Employment elasticity, defined as the rate of job creation in response to output growth should be formally integrated into national and state-level planning frameworks to ensure that economic expansion translates into broad-based employment. Reviving state-level industrial policy and embedding employment targets into fiscal and trade strategies are also essential.

6. Addressing Regional Disparities:

Though NSDP per capita was statistically insignificant, qualitative findings highlight stark regional inequalities. Targeted spatial policies are needed to address imbalances in employment opportunities, especially in eastern and central India.

Measures should include fiscal incentives for firms investing in high-unemployment states, customised skilling missions aligned with local economic structures, and decentralised job-matching services. Strengthening district employment exchanges and linking them with universities and colleges can improve access to regional labour markets. The statistical insignificance of NSDP per capita with graduate employment also suggests that regional wealth alone is not a sufficient driver of employability — policies must directly target job creation and graduate-skills alignment in underserved states.

These recommendations offer a coherent and multi-dimensional roadmap to address India's graduate unemployment crisis. They reflect the structural complexity of the issue and the need for integrated action across education, labour, and industrial policy domains.

Limitations of the Study:

While this study offers comprehensive insights into graduate unemployment, certain limitations remain. First, the regression analysis does not fully correct for potential endogeneity from reverse causality or omitted variables, limiting causal inference. Future studies could use dynamic panel models or IV approaches to address this limitation.

Second, NSDP per capita may not fully reflect intra-state disparities or the sectoral structure of growth. It also fails to capture informal activity and interregional inequality, possibly contributing to its statistical insignificance. Measurement limitations at the sub-national level may further weaken its reliability.

Third, due to data constraints, firm-level and occupation-specific variables were excluded, limiting the depth of occupational-level analysis.

Finally, the qualitative analysis is based on secondary sources, which, though thematically rich, do not reflect real-time labour market experiences.

Directions for Future Research:

Future research should explore graduate unemployment by gender, caste, and academic stream to uncover deeper labour market inequalities. Incorporating firm-level data and employment elasticity estimates across industries could sharpen our understanding of sector-specific job creation and graduate absorption.

Longitudinal studies tracking graduates over time would provide insight into dynamic transitions between education, unemployment, and underemployment. Urban-rural differences also deserve closer scrutiny, especially within states where aggregate data may obscure intra-regional disparities.

Further work could evaluate the impact of policy initiatives such as state skilling missions, NEP 2020 implementation, and public-private partnerships in technical education. Given the growing influence of digital transformation, future research should also assess the role of emerging technologies and digital skilling programmes in improving employability.

Methodologically, future econometric studies could employ instrumental variable techniques or exploit natural experiments, such as policy shifts or economic shocks to better identify causal effects. Comparative analyses of public versus private higher education institutions may also clarify variations in graduate outcomes and institutional accountability.

Together, these research avenues would enhance theoretical understanding and inform more targeted policy interventions to reduce graduate unemployment.

Final Remarks:

This paper shows that graduate unemployment in India stems not just from education levels or macroeconomic trends, but from deeper structural and institutional barriers. The findings call for a policy shift towards strengthening labour market institutions, realigning industrial strategy, and bridging the gap between education and employment.

The jobless growth paradox underscores the need to prioritise the quality and inclusivity of growth over aggregate output. By integrating empirical analysis with qualitative insight, this study provides a comprehensive framework for understanding and addressing graduate unemployment. It contributes to both academic research in development and labour economics and the practical policy dialogue on youth employment in emerging economies.

Tackling this challenge requires coordinated action among educational institutions, government, and industry to ensure that India's growing graduate population transitions successfully into the workforce, unlocking the country's **demographic dividend** and supporting **sustainable, inclusive development.**

APPENDICES

Appendix A: Description of Variables

The table describes the dependent and independent variables used in the panel data regression model.

Variable Name	Type	Description	Unit of Measurement
Graduate Unemployment Rate	Dependent Variable	Percentage of unemployed graduates in the total graduate labour force	Percentage (%)
NSDP per Capita	Independent Variable	State-level per capita income (constant prices)	Indian Rupees (₹), constant prices
Government Expenditure on Higher Education	Independent Variable	Total government expenditure on higher education	Crore Rupees (₹ crores)
Labour Market Informality Rate	Independent Variable	Share of informal workers in total employment	Percentage (%)
Services Sector Employment Share	Independent Variable	Share of national employment in the services sector	Percentage (%)
Industry Sector Employment Share	Independent Variable	Share of national employment in the industry sector	Percentage (%)
Gross Enrolment Ratio (GER) in Higher Education	Independent Variable	Enrolments in higher education as % of eligible population	Percentage (%)

Appendix B: Fixed Effects Regression Output (L2 Ridge Regression Coefficients)

The table presents results from the fixed effects panel regression (2011–2023, 33 regions). Coefficients are from L2 Ridge Regression, while standard errors and significance levels are from the original FE model.

Variable	Coefficient (L2 Ridge)	Standard Error	t-Statistic	p-value
GER in Higher Education (%)	-0.0089	0.0089	-11.576	0.0000
GDP Growth (%)	0.2509	0.0016	156.077	0.0000 ***

Labour Market Informality (%)	2.7247	0.0128	212.486	0.0000 ***
Services Sector Employment (%)	1.0616	0.0107	98.598	0.0000 ***
Industry Sector Employment (%)	-0.2484	0.0022	-115.514	0.0000 ***
NSDP Per Capita	1.41×10^{-7}	0.000000476	1.540	0.124
Constant	-278.827	1.440	-193.634	0.000 ***

- L2 Ridge Regression ($\lambda = 1\times10^{-6}$) was used to reduce multicollinearity and stabilize coefficients.
- Standard errors and significance levels are from the original Fixed Effects model.
- ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Model Summary Statistics:

Statistic	Value
R-squared	0.9864
Adjusted R-squared	0.9851
F-statistic	3930057
Prob (F-statistic)	4.4782×10^{-93}
Number of Observations	429
Degrees of Freedom (Residual)	389
Degrees of Freedom (Model)	39
Root Mean Squared Error (RMSE)	0.4593