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- Research Articles
- Book Reviews/Review Articles
- Research Notes/Commentaries
- Latest Issue/Policy Centric Database

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References

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Editorial

This issue of the *Odisha Economic Journal (OEJ)* has seven full-length articles dealing with an array of important issues in development both at the micro and macro levels. The first paper (by Priya Ranjan and Prasant Kumar Panda) using a linear multiple regression technique in a cross-sectional framework for data on 28 Indian states, explores the impact of income disparity, economic status and public expenditure on stunting among children under the age of five. The analysis observes that states where per capita income and public expenditure on health have been low, income inequality is high and women's literacy is low incidence of stunting has been pronounced.

The paper (by Subal Danta and Badri Narayan Rath) focusing on the manufacturing sector of Odisha applies the ARDL model to explore linkages between labour productivity, employment and real wages. It finds the existence of long run association among the three. While real wages positively affect labour productivity, employment affects it negatively, the study observes. In a detailed field survey-based paper (by Saida Banoo and Sanjukta Das) the authors explore the dynamics of seasonal migration mostly by workers from Dalit households from Odisha to brick kilns in neighbouring states as mediated and controlled by 'sardars' or labour contractors. The study underscores continuing exploitation of labour despite the emergence of formal institutional arrangements to curtail the same.

In order to analyse the socio-economic and spatial variation in average lifespan in Odisha the paper (by Chodaganga Sahu and Bikash Padhan) uses data from the Annual Health Survey to find that the coastal districts have a higher average lifespan while the southern districts have the lowest figure. This differential may be attributed to factors such as low levels of literacy, low monthly per capita expenditure, higher share of Scheduled Caste and Scheduled Tribe population, limited access to healthcare and higher levels of poverty.

The next paper (by Alen Joshy and P Abdul Kareem) attempts an analysis of competitiveness in cereals in the BRICS nations as under the institutional arrangement of the World Trade Organisation over a long period 1996-2020. It brings up the trade-hindering nature of non-tariff measures and makes a case for improving land quality for enhancing productivity as also income from farming in these economies.

Following a panel data approach for the period 1991 to 2023, the paper (by Anjum Sheikh, Aas Mohammad and Fayza Shahid) attempts an evaluation of the Triple Deficit Hypothesis in the emerging and developing Asian economies, namely, India, Bangladesh, China, Indonesia, Malaysia, and Pakistan. The analysis observes that as both fiscal balance and saving investment gap are highly significant variables, current account can be improved by regulating fiscal deficit and increasing domestic savings. However, it points out that the current account balance is negatively affected by the real effective exchange rate.

The following article (by R. Mariappan), considering relevant data from 1990 to 2023 attempts to analyse the asymmetric impacts of government spending on education and health on the economic growth of select states as Assam, Bihar, MP, Odisha, and Uttar Pradesh. Applying nonlinear ARDL and dynamic multiplier models the study finds presence of statistically significant asymmetric effects in both the short and long runof government expenditure on education and health expenditure on economic growth across all sample states.

This issue of the *OEJ* carries two articles as Research Note/ Commentary/ Perspectives. The first one (by Pragyan Parimita Nayak and Minati Mallick) explores the challenge of labour migration from the poorer regions of western Odisha and brings up a policy suggestion as to if promotion of micro, small and medium enterprises in these districts would address this crisis by creating opportunities for jobs and income at the local level. The second paper (by Amandeep Verma, Bhushan Singh and Sandeep Kumar) uses a DEA-Tobit approach considering relevant data for 22 districts of Haryana between 2010 and 2023 to examine the role of science and technology in promoting farm productivity and agricultural technological efficiency. The key policy implication of this exercise has been to enhance targeted investment in R&D by the state to attain both technical efficiency and sustainable farm growth in the state.

At the end, an edited volume on youth employment in India has been reviewed (by Keshab Das) discussing multiple dimensions of the pervasive challenge.

Keshab Das
Editor-in-Chief,
Odisha Economic Journal

Article

Child Stunting in India: Examining the Impact of Wealth Inequality, Economic Development, and Public Health Spending

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Abstract

The study explores the impact of income disparity, poor economic conditions, and public expenditure on stunting among children under five in Indian states. The study uses a linear multiple regression technique in a cross-sectional framework using data from secondary sources for 28 Indian states. Stunting among children under five is more common in states where per capita income and per capita public spending on health are low. Wealth inequality and women's literacy rate emerged as significant factors influencing the stunting rate.

Keywords: stunting, wealth inequality, per capita gross state domestic product, public expenditure on health, women literacy, malnutrition

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1. Introduction

Child stunting is described as low height-for-age, and itis widely used as a significant indicator of chronic malnutrition. Child stunting shows long-term inadequacies in nutrition, health, and care . Stunting has substantial implications, including decreased cognitive development, reduced educational achievement, lower economic production, and a heightened risk of chronic illnesses in adult hood (Chakraborty et al., 2024). Stunting is a major global health problem, especially in poorer regions where wealth inequality and weak economic conditions prevail. When nations grow on their economic and social fronts, it is expected that child stunting should be reduced.

India is one of the countries with a high burden of stunted children globally (Pooja & Guddattu, 2022). India has observed a significant decline in stunting rates from 48 per cent to 35.5 per cent from 2005-06 to 2019-21 through public expenditure on health and nutrition, public health initiatives, improved maternal and child healthcare, and greater nutritional awareness (Mc Govern et al., 2017; NFHS, 2006, 2016, 2021). However, the burden of stunting is still high, and there are considerable differences between states.Poorer states such as Bihar, Uttar Pradesh, Madhya Pradesh, and Jharkhand have much higher stunting rates than the progressive states like Kerala, Haryana, and Sikkim (NFHS-5, 2021).These differences may indicate deeper economic, societal, and environmental issues. Higher stunting rates in poor regions can be attributed to disparities in wealth, economic circumstances, and public health efforts. Limited resources and inadequacy of healthcare financing also exacerbate malnutrition and poverty in these regions. The contrary is true in economically prosperous regions; stronger economies and healthcare finance enable more successful stunting reduction measures (WHO, 2018). There are exceptions on both sides, which can be attributed to effective governance, efficiency in public spending, and socio-cultural stigma.

Much literature describes the strong association between vital factors and child malnutrition. Wealth inequality within a nation exacerbates the issue by concentrating resources in the hands of a few, leaving the poorest households even more vulnerable to food insecurity and deprivation. This unequal distribution limits their ability to afford diverse diets rich in micronutrients essential for growth,increasing the risk of stunting (Khan & Mohanty, 2024; Long et al., 2020). Several studies have consistently shown that children from the lowest wealth quintiles are disproportionately affected by stunting compared to their counterparts in higher wealth quintiles. This is particularly evident in low-income and middle-income nations, where economic disparities are pronounced, and public health systems cannot often mitigate the adverse effects of poverty on child health outcomes (Khan & Mohanty, 2024; Nwosu & Ataguba, 2020; Rabbani et al., 2016; Shibre et al., 2020). Countries with limited resources have limited necessary goods and services like access to health care, food, safe water, and sanitation facilities, which are determinants of child nutrition status, growth, and development (Black et al., 2013). Public spending on health is key to addressing stunting (Biadgilign et al., 2019; Kohli et al., 2020). Adequate investment in health and nutrition services can improve maternal and child health, increase immunisation coverage, and provide supplementary nutrition through Integrated Child Development Services (ICDS). However, in several states, especially those with lower economic capacity, public health expenditure is insufficient, and there is limited allocation to nutrition-specific programs. This low spending leads to inadequate reach and coverage of nutritional schemes and questions the effectiveness of interventions to reduce stunting (Biadgilign et al., 2019; Chakrabarti et al., 2019; Narayan et al., 2019; Ranjan & Panda, 2022). Several studies found that poor economic conditions at the state level, reflected in low percapita GSDP, further worsen the problem (Ahluwalia, 2016; Mundle et al., 2016). States with lower economic output per person have reduced capacity to invest in essential public services, including health and nutrition programs (Balani et al., 2023). This translates to weaker healthcare infrastructure, limited access to quality healthcare services, and inadequate social safety nets for vulnerable families (Kruk et al., 2018). Consequently, children in these states are more likely to experience repeated infections, inadequate diet, and limited access to preventive and curative health interventions, and all of them contribute to stunting.

Despite the extensive research on child malnutrition, there are still significant gaps in comprehending the interconnected roles of income disparity, poor economic circumstances, and low governmental spending in determining the stunting burden among children in Indian states. Though research concentrates on the socioeconomic drivers of malnutrition,examining the influence of state-level spending and inequality is important. Furthermore, national-level analysis often shows aggregate trends but fails to capture the state and regional disparities, especially between poor and rich states. The interconnectedness of wealth inequality, poor economic conditions, and public health expenditure as predicting determinants of stunting are not often studied together. This gap limits the ability to design comprehensive interventions.

In this work, an attempt is made to see the pattern of association of stunting in the states with their wealth inequality, per capita income, and public health spending and examine the influence of these critical state-level factors on the stunting of children under the age of five.

The organisation of the rest of the work is outlined as follows: In Section 2, the paper elaborates on the data and methodology employed in the research. Results are discussed in Section 3. Section 4 offers conclusions and suggestions.

2. Data and Methodology

The study uses secondary datafrom 28 Indian states. The data have been compiled from the National Family Health Survey-5 (NFHS 5) and Economic and Political Weekly Research Foundation (EPWRF) to analyse the objectives.In order to understand the key factors of child malnutrition burden in Indian states, the study used the stunting rate among children under five as the dependent variable based on NFHS-5 (2019-21). Stunting is widely used as a pre-dominant indicator for understanding malnutrition. The stunting data are available for 2019-21, the study period of NFHS-5, and the financial year 2020-21 being the year of COVID-19. We have used state per capita income and per capita health spending for 2019-20. As we aim to check the influence of economic disparities on children's nutrition, the states are categorised into Low-Income States (LIS), Middle-Income States (MIS), and High-Income States (HIS) based on the percentile of percapita GSDP for 2019-20. States with per capita income up to or below the 33rd percentile are categorised as LIS. Similarly, states with per capita income in the 34 to 66 percentile bracket are categorised as MIS, and thosein the upper remaining percentile are categorised as HIS (Jami, 2018; Purohit, 2004). The classification of states based on this is given in Appendix Table I.

The study has employed linear multiple regression techniques in a cross-sectional framework to examine the determinants of stunting among children under five in Indian states. The study examines socioeconomic variables such as Wealth-Gini, per capita health expenditure, women's literacy rate, and coverage with all basic vaccination rates described in Table1.Women's literacy and coverage with all basic vaccination ratesareused as control variables.

The variables areselected based on their relevance in determining the stunting rate among children under five. Income inequality, as measured by the Gini coefficient of household wealthfor the state, measures disparities in access to wealth across states. States with high Gini indicate greater wealth inequality, which is expected to be associated with higher stunting (Khan & Mohanty, 2024). Higher per capita income is often associated with improved access to food, healthcare, and sanitation. So, states with high per capita GSD Pare likely to correlate with lower stunting rates (Büttner et al., 2023). Higher per capita health expenditure in the states indicates better access to health infrastructure and healthcare (Varkey et al., 2020), essential in dealing with malnutrition. Higher coverage withall basic vaccinations is expected to be associated with lower stunting (CBGA India, 2017). Furthermore, women's education has improved childcare and nutrition practices (Panda & Rout, 2007; Panda & Subudhi, 2020). States with higher women's literacy rates are expected to be associated with lower stunting (Black et al., 2013).

Initially, per capita GSDP has been included in the model to analyseits impact on stunting. However, due to its high correlation with other explanatory variables, it was excluded from the final model to avoid the problem of multicollinearity. The basic model aims to examine the key determinants of stunting as follows:

$$STUNT_i = \beta 0 + \beta 1(WGC)_i + \beta 2(LPCHE)_i + \beta 3(WLR)_i + \beta 4(CWBV)_i + \varepsilon_i$$

where,

STUNT: Stunting rate under children under 5

WGC: Wealth-Gini Coefficient of the household for states

LPCHE: Log of Per Capita Public Health Expenditure

WLR: Women's Literacy Rate

CWBV: Coverage With all Basic Vaccinations

å: Stochastic error term

i: The observation unit

Table 1: Descriptive Statistics

	Stunting	Wealth-Gini	PCHE	WLR	CWBV
Obs	28	28	28	28	28
Mean	32.01	0.17	3190.68	76.91	76.39
Min	22.3	0.1	1104.73	55	91
Max	46.5	0.27	7311.51	97.4	58
Std. Dev	6.12	0.05	1837.11	10.68	8.1

Source: Authors' calculation using STATA.

The description of all variables stated in the model has been given in Table 2, and descriptive statistics of the variables utilised have been provided in Tables 1 and 3. An ordinary least square technique is used to estimate the regression coefficients. The coefficient of variation (CV) is shown in Table 3. The relative variability of a dataset can be understood using CV. It is useful for comparing dataset dispersion. It is calculated by dividing the standard deviation by the mean. When the CV is small the data is more concentrated around the mean (Kasiviswanathan et al., 2023). The greater the CV, the more spread out the data are from the mean. The CV ranges are a standardised method for comparing the variability of different datasets. The variability has been classified as: less (if CV d”0.20), moderate (0.20 < CV d”0.30),high (0.30 <CV d”0.50), and very (if CV > 0.50) (Kasiviswanathan et al., 2023).

The variance inflation factor (VIF) has been employed to check the multicollinearity among the variables, and the Breush Pagan test is applied to check heteroscedasticity in the model. Table 5 shows no evidence of heteroscedasticity in the data set.

Table 2. Description of Variables

Variable	Abbreviation	Description	Unit	Source
STUNT	Stunting	Stunting rates among children under 5	Per cent	NFHS-5 (2019-21)
Wealth-Gini Co-efficient	WGC	The Gini coefficient measures wealth disparity within a population. It ranges from 0 to 1, with 0 representing perfect equality (everyone has the same income or wealth) and 1 representing perfect inequality (one person has all of the income or wealth).	Index	NFHS-5 (2019-21)
Log of Per Capita Health Expen-diture	LPCHE	PCH is obtained by dividing its total health expenditure by its population. Then, it was converted into a log.	Numeric	EPWRF (2019-20)
Women Literacy Rate	WLR	The study assumes that women aged 15-49 who have completed standard nine or higher are literate. While all other respondents could read a sentence, they were considered illiterate.	Per cent	NFHS-5 (2019-21)
Coverage	CWBV	Percent of children aged 12-23 months who had received basic vaccines before the survey. To be considered for all basic vaccinations, a child must have received at least one dose of BCG vaccine, three doses of DPT vaccine, three doses of polio vaccine, and one dose of measles vaccine.	Per cent	NFHS-5 (2019-21)

Source: Compiled by authors from NFHS and EPWRF

3. Results

Section 3.1 presents a pattern of disparities ineconomic indicators, health expenditure, and stunting rates for different Indian states.

3.1 Analysis of Crucial Indicators and Child Nutrition Outcomes

Table 3 presents a comparative analysis of economic indicators, public health expenditure, health services, and nutritional outcomes (stunting) across three categories of Indian states: LIS, MIS and HIS. Table3 examines and compares these metrics across the regions.

Table3: Economic Indicators, Public Health Expenditure, Health and Nutrition Services, and Outcome

State Cate-gory	States	PC GSDP (INR)	PCHE (INR) (%)	Wealth quintile (Lowest)	Wealth quintile (Highest)	Women's literacy rate	Coverage With all Basic Vaccina tions (%)	Stunting (%)
LIS	Bihar	48263	2573.1	42.8	5.4	55	71	42.9
LIS	Uttar Pradesh	74679	3136.6	23.9	17.8	66.1	70	39.7
LIS	Jharkhand	82276	4638.8	45.9	7.5	61.7	74	39.6
LIS	Manipur	86681	2086.2	18.3	7.8	85.3	69	23.4
LIS	Assam	100501	6743.4	38.1	4.1	75.1	67	35.3
LIS	Meghalaya	106267	3039.9	31	4.2	87.6	64	46.5
LIS	Madhya Pradesh	111927	2140.2	31.5	15.1	65.4	77	35.7
LIS	Odisha	118903	4442.7	35.1	8.7	69.5	91	31
LIS	Chhattisgarh	119066	1104.7	29.9	11.7	72.5	80	34.6
LIS	West Bengal	121232	1806.1	32.7	7.7	72.9	88	33.8
MIS	Rajasthan	128451	1328.4	13.3	21.6	64.7	81	31.8
MIS	Tripura	134973	3379.3	31.6	2.5	78.3	70	32.3
MIS	Nagaland	137510	5828.6	27.6	7.4	83.4	58	32.7
MIS	Punjab	173119	4834.2	1.1	60.6	79.4	76	24.5
MIS	Andhra Pradesh	179280	1923.4	5.2	15.6	66.7	73	31.2
MIS	Arunachal Pradesh	198701	2357.3	23.3	4.9	71.3	65	28
MIS	Mizoram	208594	4593.7	6.6	24.8	94	73	28.9
MIS	Uttarakhand	213304	1106.8	5.9	33.6	79.8	81	27
MIS	Maharashtra	216319	1429.1	8.6	27.9	82.3	74	35.2
HIS	Himachal Pradesh	217229	1881.2	3.8	28.9	90.7	89	30.8
HIS	Tamil Nadu	229657	7202.2	4.8	24.6	84	89	25
HIS	Kerala	233338	2009.7	0.8	40.1	97.4	78	23.4

HIS	Gujarat	238978	7311.5	12.2	27.4	73.4	76	39
HIS	Karnataka	244437	1167.1	7.3	19	73.4	84	35.4
HIS	Telangana	254402	3032.8	5.1	22.2	64.8	79	33.1
HIS	Haryana	258006	2680.4	2	47.7	79.7	77	27.5
HIS	Sikkim	471379	2604.6	2.7	12.8	87.1	83	22.3
HIS	Goa	485645	2955.6	0.5	61.3	92.2	82	25.8
	India	185468.5	3190.6	17.5	20.4	76.9	76.3	32.0
	LIS	96979.5	3171.1	32.9	9.0	71.1	75.1	36.2
	MIS	176694.6	2975.7	13.6	22.1	77.7	72.3	30.1
	HIS	292563.4	3427.2	4.3	31.5	82.5	81.8	29.1
	Max	485645	7311.5	45.9	61.3	97.4	91	46.5
	Min	48263	1104.7	0.5	2.5	55	58	22.3
	CV	0.5	0.6	0.8	0.7	0.1	0.1	0.2
	SD	103200.7	1837.1	14.5	16.2	10.6	8.1	6.1

Source: Compiled by authors from EPWRF and NFHS-5

It has been observed from Table 3 that the per capita income of LIS is INR 96,979.50 compared to INR 1,76,694.60 for MIS and INR 2,92,563.4 for HIS for 2019-20. This shows that per capita income in LIS is much lower. Also, LIS has a much lower public expenditure (INR 3,171.18) than HIS (INR 3,427.27). Furthermore, it has been observed that in LIS, as high as 32.92 per cent of the households of states fall into the lowest wealth quintile, much greater than in MIS (13.68 per cent) and HIS (4.35 per cent). This suggests that a larger portion of households in LIS are in the lowest wealth quantile compared to the same MIS and HIS. Additionally, in LIS, just 9 per cent of households belong to the top wealth quintile, compared to 22.21 per cent in MIS and 31.55 per cent in HIS. Around 75.10 per cent of children in LIS have received all basic vaccinations, which is lower than the recorded HIS percentage of 81.80 per cent. Women's literacy rate is low in LIS (71.11 per cent) as compared to MIS (77.76 per cent) and HIS (82.52 per cent). It is observed that states with higher levels of women's literacy tend to have lower rates of child stunting, regardless of their economic classification as LIS or HIS. This suggests that maternal education plays a critical role in improving child nutrition. It has been noted that LIS has the highest stunting rate at 36.25 per cent, which is much higher than MIS (29.68 per cent) and HIS (29.63 per cent). This suggests that low-income states are more vulnerable to stunting.

The inter-state comparison shows that LIS states like Bihar, Uttar Pradesh, and Jharkhand have the lowest PCGSDP, a high percentage of people belonging to the lowest wealth quintile, and the highest stunting rates. This indicates that poverty and low economic development may be major contributors to stunting in these regions. As we move up the income ladder, stunting rates generally decline. For instance, states like Andhra Pradesh and Tripura have higher PCGSDP than LIS states and exhibit lower stunting rates (around 30 per cent). States with the higher PCGSDP, such as Kerala, Goa,and Sikkim, have the lowest stunting rates (below 25 per cent). This suggests that better economic conditions can significantly improve child nutrition outcomes. Furthermore, there is no consistent pattern between per capita GSDP and stunting. For example, Manipur has a low per capita GSDP and stunting rate. This is because, over the past decade, access to healthcare in Manipur has improved, there is high women literacy rates, effectiveness of public spending and socio-cultural factors along with significant progress in house hold sanitation facilities. Additionally, higher levels of education among women have contributed to better child nutrition outcomes (NITI Aayog, 2022). Meanwhile, Maharashtra and Gujarat have high per capita GSDP and health expenditure, but high rates of stunted growth. It is due to inefficiencies in the delivery system and administrative bottlenecks that hinder the effective implementation of nutrition interventions (CBGA India, 2017). Also, economic disparity, inadequate diet, and limited healthcare access in Gujarat and Manipur contribute to children's nutritional status issues, potentially leading to high stunting rates (Sahu, 2018). LISs with low per capita health expenditure have high stunting rates, except in Manipur. This underscores the need for increased investment in public health infrastructure and services in these states. Moving from LIS to MIS and HIS, it has been observed that a high per capita health expenditure is associated with lower stunting rates. This highlights the positive impact of investing in public health on child nutrition.

Overall, Table 3 shows apparent economic and health differences across different income groups of states in India. LIS states remain the most disadvantaged, with the lowest per capita GSDP, health spending, vaccination coverage,women literacy rate, and high wealth disparity, which lead to the worst incidence of child malnutrition. MIS states fall in the middle but still have low per capita income and per capita health spending compared to HIS.

3.2 Empirical Results

In this section, an attempt has been made to examine the determinants of stunting rates among children under five. Table 4 shows regression coefficients of stunting in Indian states. F-statistics (6.9*) suggestthat the overall model is statistically significant. R-Square (0.47) indicates that the independent variables in the model can explain approximately 47 per cent of the variance in stunting rates.

Table 4: Regression Result

Variables	Coefficient	t-value	p-value	(95% Confidence Interval)
WGC	58.71	2.96	0.007*	[17.69, 99.76]
LPCHE	.11	0.07	0.9	[-3.17, 3.97]
WLR	-.16	-1.79	0.08***	[-0.35, 0.02]
CWBV	-.11	-0.9	0.37	[-0.34, 0.13]
C	48.6	1.4	0.17	[-23.16, 120.4]
AdjR-Square			0.47	
F statistics			6.9*	
No. of observation			28	

Authors calculated using data from RBI, NFHS, and EPWRF

*1% level of significance,**5% level, and ***10% level.

It has been observed from the regression results that Wealth Gini and women's literacy rate are statistically significant in influencing the stunting rate. States with higher wealth inequality have a higher rate of stunting. A higher Gini coefficient, indicating greater inequality, is associated with higher stunting rates among children under five. This suggests that economic inequality substantially impacts child nutrition and health outcomes.It is evident that when a higher proportion of households in states remain with a lower wealth quintile, the ability of people to spend on health and nutrition would be limited. Here, the wealth disparity findings are similar to those observed in the pattern analysis. Wealth-Gin iemerged as a significant determinant for stunting for those under five. Even if per capita GSDP is included in the estimation model, wealth Gini still emerges as a potential predictor of stunting. So, the states should take initiatives to improve the wealth holdings of households in the lower strata.

It is observed that when women's literacy rate increases by one per cent, the stunting rate reduces by 0.16 per cent. Higher women's literacy is linked to lower child stunting. Educated mothers are more likely to have better knowledge of nutrition, hygiene, and healthcare practices, which can contribute to improved child health outcomes. Variables such as per capita health expenditure and coverage with all basic vaccinations did not emerge significant in influencing stunting in children under five. However, an analysis with many observations, typically in a panel structure, may provide different results for these variables.

The necessary post-estimation tests have been conducted to check possible regression problems in the data set. Table 5 shows the results of the Breusch-Pagan test. The test finds no indication of heteroscedasticity (p = 0.29), implying that the model's residuals have constant variance. As per capita GSDP was highly correlated with other independent variables, the same was dropped from estimation. The mean VIF in the revised estimation is 1.27 (Table 6). This suggests that no serious multicollinearity problem arises in the model.

Table 5: Heteroscedastic Test

Breush Pagan test	
Ho: Constantvariance	variables: the fitted value of stunting among children under 5
Chi-Square	1.1
Prob >Chi-square	0.29

Source: Authors'calculations using STATA.

Table 6: Multicollinearity Test

VIF Results		
Variable	VIF	1/VIF
Wealth Gini	1.47	0.67
WLR	1.32	0.75
CWBV	1.21	0.82
LPCHE	1.07	0.93
Mean VIF	1.27	

Authors' calculation using STATA

4. Conclusion

The main objective of the study was to verify the impact of wealth and income inequality on the prevalence of malnutrition among children in Indian states. Besides, the study also examines the implications of state intervention through public spending on nutrition. It is observed from the pattern analysis that stunting among children under five is more common in states where per capita income and per capita public spending on health are low, and a greater percentage of the households live in the lowest wealth quintile. Wealth inequality emerged as one of the important factors in influencing the stunting rate among children under the age of five in Indian states. States with higher wealth Gini coefficients have higher stunting rates. In low-income states, a high percentage of households are under the lowest wealth quintile, and stunting rates are very high in these states. Though some of the low-income states are allocating more health expenditure to nutrition, their stunting rates are still high. This suggests that health expenditure alone is not sufficient without systemic improvements in health infrastructure, service quality, and addressing wealth inequality. So, there is a need for comprehensive policy strategies to reduce wealth disparities, increase women's literacy, and well-designed government welfare schemes, especially in LIS, to reduce stunting in children under five.

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Appendix

Appendix Table I: Category of Indian States

State Category	States
Low-income States	Bihar, Uttar Pradesh, Jharkhand, Manipur, Assam, Meghalaya, Madhya Pradesh, Odisha, Chhattisgarh, and West Bengal.
Middle-income States	Rajasthan, Tripura, Nagaland, Punjab, Andhra Pradesh, Arunachal Pradesh, Mizoram, Uttarakhand, and Maharashtra.
High-income States	Himachal Pradesh, Tamil Nadu, Kerala, Gujarat, Karnataka, Telangana, Haryana, Sikkim, and Goa.

Article

Nexus between Labour Productivity, Real Wage and Employment: Evidence from the Manufacturing Sector of Odisha

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Abstract

This paper investigates the nexus between labour productivity, employment, and real wages in the registered manufacturing sector in Odisha. To do so, we use disaggregated panel data of all manufacturing industries of Odisha by taking annual data from 1980-81 to 2018-19. By employing a Panel Auto Regressive Distributive Lag (ARDL) model,the study finds a linkage between labour productivity, employment and real wages in the long run but no substantial relationship among these variables in the short run. It further reveals that real wages positively affect labour productivity, but employment negatively affect labour productivity. From a policy perspective, proper coordination between these indicators at the industry level is required to maintain the stable performance of Odisha's manufacturing sector.

Keywords: Labour Productivity, Real Wage, Panel Unit Root, Panel ARDL, Manufacturing Sector, Odisha

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1. Introduction

Wage policy and labour market structures must be considered appropriately to develop sustainable economies and evenly distributed societies. Improving productivity is crucial for achieving higher economic growth and ensuring its stability over time. Labour productivity serves as a stimulus for the nation's economic growth and improves the welfare of the workforce (Fachin & Gavosto, 2010). With a plentiful labour supply, the country may grow by increasing labour productivity, creating jobs, and providing suitable remuneration to its workers (Haltiwanger et al., 1999). Furthermore, linkage between labour productivity, employment and real wages in manufacturing sector sets foundation to achieve sustained long-term economic growth. Higher labour productivity also enhances profit because of lower per unit manufacturing cost (Samargandi, 2018). Therefore, comprehending the interconnection among these variables is crucial for achieving manufacturing-led growth in a labour-surplus economy like India. Economic growth supported by adequate employment opportunities and improved labor productivity fosters inclusivity. This, in turn, lays a strong foundation for transitioning from domestic to global market integration, which is crucial for enhancing competitiveness and economic resilience.

Several studies have been conducted globally and nationally to investigate the relationship between labour productivity, real wages, and employment levels. However, literature on this issue is scarce, particularly in Odisha's manufacturing sector. Odisha is one of India's lower industrial base states and has significantly progressed in economic growth over the last decade. The manufacturing sector plays a key role in the overall growth performance of Odisha. Therefore, examining linkages between labour productivity, employment, and real wages in the sector will reveal its performance and help formulate policies to strengthen it further.

The primary objective of the study is to assess the relationship between labour productivity, real wages, and employment in the manufacturing sector in Odisha. To examine this objective, we employ Panel ARDL and Panel Error Correction Model (ECM) techniques. The Panel ARDL and Panel ECM techniques are more suitable for identifying the long-run and short-run nexus among these variables. The study discovers that real wage and labour productivity is positively and strongly related. On the other hand, we find a negative and substantial relationship between labour productivity and employment. The study does not find any relationship between these variables in the short term.

The study is organised as follows: Section 2 illustrates a broad overview of Odisha's manufacturing sector; Section 3 briefly discusses theoretical and empirical literature; Section 4 describes the data and methodology; Section 5 presents the empirical results; and Section 6 highlights concluding remarks.

2.Overview of Odisha's Manufacturing Sector

The industrial sector plays a key role in any economy since it has more forward and backward linkages than agriculture and tertiary sectors (Hirschman, 1971). In the context of Odisha, the industrial sector contributes significantly to the state's overall development by driving economic growth and fostering intersectoral linkages. Also, within the industrial sector, the manufacturing segment holds particular importance as it serves as a cornerstone for Odisha's industrial development (Rath & Bhattacharya, 2011). Odisha's industrial growth, with an impressive annual rate of 11.5%, far outpaces India's overall industrial growth, which hovers around 5% in recent years (MoSPI, 2023). Odisha manufacturing sector's share to India's manufacturing gross value added (GVA) has risen from 2.9% in 2011-12 to 4.2% in 2022-23, highlighting its growing role in the national industrial landscape. India's manufacturing sector has grown steadily, but its progress and share in the economy have been relatively slow. (*Odisha Economic Survey, 2022-23*). Odisha has emerged asa viable place for industrial expansion because of abundant natural resources, a strategic position, cheap labour force, and successful government initiatives (Finance Department, Govt. of Odisha, 2022). Even though agriculture dominates the Odisha economy, the industrial sector contributed approximately 32 per cent of State Gross Domestic Product (SGDP), followed by the state's service sector *(Economic Survey of Odisha, 2021-22).*

In addition to the aforementioned findings, the state's labor participation also demonstrated a notable increase, rising to 56.5% in 2020-21 compared to 55.3% in 2019-20 and 51.2% in 2018-19. This progression reflects a sustained improvement in the proportion of the total labor force actively engaged in economic activities during the above-mentioned period. (Periodic Labour Force Survey, 2020-21). In line with the above trend, the manufacturing sector also employed around 28.47% of the state's total labour force in 2020-21 (Industrial Promotion and Investment Corporation of Odisha Limited, Govt. of Odisha, 2022).

Table 1: Share of Gross Value Added and Employment in Manufacturing, Odisha

NIC Code	1981	1991	2001	2011	2019	1981	1991	2001	2011	2019
	GVA (in %)					Employment (in %)				
10	3.3	2.5	4.3	4.4	3.7	10.5	12.1	6.9	10.3	8.6
11	0.0	0.1	0.7	0.8	1.4	0.1	0.5	0.9	1.0	1.9
12	0.4	0.1	0.2	0.2	0.1	0.1	0.1	0.1	0.4	0.1
13	4.6	2.7	0.8	0.1	0.1	11.8	12.8	8.4	0.9	0.7
14	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.0	0.0	1.0
15	2.4	0.0	0.0	0.0	0.0	1.8	0.2	0.0	0.0	0.0
16	1.5	1.1	0.7	0.1	0.0	3.3	2.2	1.3	0.4	0.2
17	8.7	5.7	5.9	2.5	2.9	10.1	6.3	6.5	2.3	2.8
18	0.0	0.0	0.0	0.2	0.1	0.0	0.0	0.0	0.3	0.4
19	0.7	0.2	0.8	1.1	2.5	1.7	0.4	0.4	0.9	3.0
20	0.0	6.5	4.1	6.8	16.7	0.2	5.5	7.0	3.4	2.6
21	0.3	1.2	0.6	0.1	0.0	2.2	2.4	2.2	0.2	0.2
22	1.8	2.2	3.9	1.1	0.8	1.1	1.7	4.5	1.8	1.7
23	10.7	11.7	8.7	5.8	3.2	16.3	14.7	10.1	8.9	6.2
24	59.2	60.1	66.5	75.7	65.8	35.5	33.4	36.9	63.2	62.0
25	0.6	1.2	0.9	0.4	0.8	1.5	3.4	2.2	1.5	1.9
26	0.0	0.5	0.0	0.0	0.0	0.0	1.0	0.1	0.0	0.0
27	1.6	1.0	0.5	0.5	1.2	0.9	1.4	1.0	0.7	1.3
28	3.9	2.0	1.2	0.0	0.5	2.1	2.7	1.7	0.3	1.0
29	0.0	0.0	0.1	0.0	0.0	0.0	0.1	0.2	0.1	0.2
30	0.1	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.4
31	0.2	0.1	0.2	0.2	0.0	0.7	0.4	0.8	0.2	0.3
32	0.0	1.0	0.0	0.0	0.0	0.0	1.7	0.0	0.0	0.0
Total	100	100	100	100	100	100	100	100	100	100

Source: Authors' calculation from Annual Survey of Industries (ASI)

To gain a thorough picture of Odisha's manufacturing sector, we evaluated its gross value added and total number of people employed overtime. Table 1 provides a comprehensive overview of Odisha's manufacturing industry regarding gross value added and employment from 1981 to 2019. The contribution of Odisha's industrial sector to gross value added and employment exhibits an uneven distribution across the various manufacturing industries. Only four industries namely basic metals, non-metallic minerals, food items, and paper products were found to be the most prominent in the state. These 4 industries account for over 70% of the manufacturing sector's total gross value added. These four major industries also account for over half of manufacturing employment. It is also evident that the industry with the highest value-addedabsorbs the most workers from the economy. The share of basic metal is highest in gross value added and manufacturing employment, while other manufacturing sectors contributed the least. The other 19 industries have a minimal proportion of gross value added and employment. The initial statistics show that the manufacturing sector's performance is unimpressive for Odisha's growth. Although Odisha has made progress in overall industrial development, the distribution of growth remains uneven across the states. This raises an important question: why does the growth of the manufacturing sector not align with improvements in labour productivity and overall employment in the state? To address this concern, this study explores the relationship between labour productivity, real wages, and employment, aiming to provide insights into the factors affecting Odisha's economic and industrial development.

3. Review of Literature

3.1. Theoretical Review

This section presents literature on the nexus between productivity, wages and employment. The starting point of the theoretical linkage between these three variables is based on the theory of wages and productivity. Theoretical models on wagescan be divided into two categories: traditional theory and modern theory. Traditional theories include the natural wage, wage fund, wage exploitation, marginal productivity, and collective bargaining theories. On the other hand, modern theories include the purchasing power theory, the theory of the natural rate of unemployment, the insider-outsider theory, the efficiency wage theory, and the implicit labour contract theory (Kormaz, 2021). According to the classical school of thought, changes in real wages do not influence labour productivity because of the assumption of homogeneous labour and the concept of wage-price flexibility (Flemming, 1987). In response to the traditional ideas, Philips (1958) discovered a strong link between the real wage and unemployment in his seminal work. These theories broadly indicate a mixed relationship between labour productivity and wages, as some theories show a positive and direct link, and others show a negative relationship between wages and productivity.

According to the natural wage theory, the minimum wage (or subsistence wage) required for workers' survival is the primary determinant of labour demand and, by extension, labour productivity (Ricardo, 1817). Similarly, in wage fund theory, the major component that contributes to labour demand is the producer's total wage fund. In this case, the wage rate is determined as a ratio of the entire wage fund to the total number of workers. The entire amount of output produced and capital accumulation in the previous year also influence the volume of wage funds (Mill, 1848). Marginal productivity theory is another important hypothesis that determines the link between wage and labour employment. According to this, the marginal product of labour is the primary determinant of labour demand. The theory discovers evidence of a positive and significant relationship between the marginal product of labour and employment (Vaggi et al., 2003). The collecting bargaining theory of wages discusses numerous elements outside labour demand and supply in setting wage rates in the economy. The fundamental determinant of wagesis the negotiation between employers and employees (Webb,1906). All of the theories described above suggest that wages tend to migrate to their equilibrium point. Under the neoclassical framework, the basic rationale for the claim is based on homogeneous labour and wage-price flexibility.

The purchasing power theory, on the other hand, was established to determine wages in response to the neoclassical theory. According to this hypothesis, a lack of effective demand is the leading cause of unemployment. As a result, wage adjustments do not sufficiently modify the economy's demand for labour. If workers' income and purchasing power are high, there will be a high demand for labour. The inverse of the foregoing mechanism will result in unemployment in the economy (Kregal, 1983). According to the natural rate of unemployment theory, the labour market will tend to achieve full employment on its own as long as wages are flexible and government interference is restricted. The natural rate of unemployment argument refutes the concept that high inflation can cause unemployment to fall. Furthermore, the theory aims to find a trade-off between unemployment and inflation (Lazear, 1986).The New Keynesian economics established insider and outsider hypotheses to explain the wage-productivity relationship. This theory describes the mix of unemployment in various sectors and the relative wage structure in a heterogeneous labour market (Lindbeck & Snower, 1986). While investigating the relationship between wages and productivity, the efficiency theory of wages discovers the critical role of productivity in changing wages. According to this hypothesis, paying workers above the market-clearing wage assists businesses in reducing staff turnover, limiting waste, and eventually boosting productivity. The implicit labour contract theory seeks to explain how legal but informal agreements between employers and employees affect the economy. According to this theory, implicit agreements play a significant role in deciding how long-term connections between employees and firms form (Patrias, 1994).

3.2. Empirical Review

A vast literature exists on the relationship between productivity, wage, and employment. Labour productivity, which also acts as the strongest long-term indicator of economic growth, significantly influences the level and quality of life across society. The link between labour productivity and wages demonstrates the interdependence of production, distribution, and consumption. Using panel cointegration techniques, Narayan & Smyth (2009) evaluated the connections between inflation, real wages, and productivity growth for the G7 countries from 1960 to 2004. They found a statistically significant positive relationship between real wages and productivity growth. Strauss & Wohar (2004) examined the long-run relationship between inflation, real wages, and productivity for a panel of 459 US manufacturing industries between 1956 and 1996. The study found that inflation can influence productivity over time, while productivity and real wages affect each other in both directions. Alexander (1993) uncovered empirical evidence that inflation, real wages, and productivity have a cointegrating connection in the United Kingdom, meaning that higher wage rates improve labour productivity through the efficiency wage argument.

Erenburg (1998) examined the long-term link between real wages and productivity in the United States from 1948 to 1990 and discovered a long-term and counter-cyclical relationship.

Apart from the studies mentioned above, numerous other studies on real wages and labour productivity also reveal a positive and significant relationship between them. One study on the Indonesian manufacturing sector discovers a decoupling tendency between real wages and productivity. The study also discovers a favourable relationship between real wages and employment in large-medium manufacturing firms (Tadjoeddin, 2016). Klein (2012) discovered that employment growth in South Africa had been partially restrained by an extended rise in the real wage, which has outpaced labour productivity growth. In addition, the analysis reveals evidence of co-integration between the real wage and labour productivity only in the long run. Another Malaysian manufacturing research looks at the same dynamic link between the real wage and labour productivity in the short and long run. Using the Error Correction Mechanism model, the study discovered that a rise in the real wage surpasses an increase in labour productivity, increasing the unit cost of labour in the long run. The study also discovers a negative relationship between real wages and manufacturing sector unemployment (Lee-Peng & Yap, 2001).

Incorporating a sectoral approach, Katovich & Maia (2018) get access to the dynamic relationship between wage and labour productivity. The study also investigates the elements that contribute to the above-mentioned disparity in Brazil from 1996 to 2014. The study discovered that labour formalisation and the minimum wage substantially affected the discrepancy. This study, like prior studies, discovered evidence of a positive relationship between wages and labour productivity. In the Turkish manufacturing sector, there has been a continuous and large discrepancy between the real wages and the marginal productivity of workers. The authors attribute the above-mentioned gap to the importance of the unemployment rate between 1950 and 2009 (Elgin & Kuzubas, 2012). Examining the determinants of labour productivity at the country level, Samaragandi (2018) found a negative and significant association between employment and compensation with labour productivity using dynamic OLS and fully modified OLS. The study also finds the positive and influential role of human capital and capital on labour productivity from 1980 to 2014 in the sample countries. In the context of an Indian manufacturing firm, studies have discovered a long-run relationship between labour productivity, real wage, and employment. Using a panel cointegration model, the findings were derived from India's two-digit manufacturing industries from 1973-74 to 1999-2000. Studies also endowed with long-run cointegration exist between productivity and wages and between productivity and employment (Bhattacharya et al., 2011).

A significant portion of existing studies investigating the interconnections among real wages, labor productivity, and employment have predominantly focused on the manufacturing industry of India. Almost all of the research found a positive and substantial relationship only in the long run. Literature has failed to identify a significant relationship in the short run and also in the manufacturing sector of Odisha. The present study examines the link between real wages, labour productivity, and employment in Odisha's manufacturing sector.

4. Methodology and Data

A Panel ARDL model is used to examine the objective of this study. Before employing the Panel ARDL and ECM, the study first checks the stationarity of these variables. The study uses Panel unit root tests such as the Levin-Lin-Chu test (Levin et al., 2002), the Breitung test (Breitung, 2000), the Im-Pesaran-Shin test (Im et al., 2003), and the Fisher-ADF (Choi, 2002) test. The Panel ARDL cointegration test examines the long-run relationship between labour productivity, employment, and wages in the second step. The Panel ARDL model is more appropriate and flexible because it considers a mixture of I(0) and I(1) orders of variables. The ARDL model, often known as the Bounds test, is widely used for describing dynamic interactions between variables, particularly in cointegration analysis. It is beneficial for dealing with non-stationary time series data, which is common in economic and financial data. The Panel ARDL model has been used to extend the ARDL model to panel data, which covers both cross-sectional and time-series dimensions. To utilise the Panel ARDL, the number of time periods in the panel sample should be greater than the number of cross-section industries (Pesaran et al., 1999). This allows for the examination of the relationship between variables while taking individual and time-specific effects into account. Again, the Pooled Mean Group (PMG) method, which is used in this study, allows for short-run parameter variation between industries while requiring long-run values to be homogeneous

(Pesaran & Shin, 1995; Pesaran et al., 1999). In this case, we employed the Panel ARDL model, and the fundamental equation is as follows:

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \ldots + \beta_k X_{kit} + \alpha Y_{it-1} + \gamma_1 X_{1it-1} + \gamma_2 X_{2it-1} + \ldots + \gamma_k X_{k\,it-1} + \mu_i + \lambda_t + \tilde{o}_{it} (1)$$

In equation (1), i narrates the cross-sectional unit, t is the time period, and k represents the optimal lags. Y is the dependent variable, which depends on explanatory variables (Xs) and lagged variables (X_{t-1} and X_{t-2}). The coefficients for the lagged independent variables are $ã_s$. The individual and time-specific effects have been explained by $ì_i$ and $ë_{t,}$ respectively. Finally, the error terms are represented by $õ_{it}$. The dependent variable (Y_{it}) is Labour productivity, defined as gross value added per unit of labour. The industry's actual wages and total employment heavily influence this labour productivity. The final empirical equation can be rewritten as follows:

$$LP_{it} = \beta_0 + \beta RW_{it} + \beta 2\ EMP_{it} + \alpha LP_{it-1} + \gamma_1 RW_{it-1} + \gamma_2\ EMP_{it-1} + \mu_i + \lambda_t + \tilde{o}_{it} \quad (2)$$

In addition to the foregoing, the study employed a ECM to assess the rate of adjustment in the dependent variable due to the shock. This rate of adjustment usually coincides with the convergence of the dependent variable to the long-run equilibrium (Johansen, 1985). A negative and substantial value indicates a long-term relationship between the dependent and independent variables. The following equation 3 is the description of the ECM equation:

$$\Delta LP_{it} = \varphi_i (LP_{it-1} \text{"} \beta_0 X_{it}) + \text{“}^{p-1}_{j=1}\ a\ *_{ij} \Delta LP_{it-j} + \text{“}^{q-1}_{j=0}\ \delta * ij' \Delta X_{it-j} + \mu_i + \varepsilon_{it} (3)$$

4.1. Data and Measurement of Variables

The annual data from the Annual Survey of Industries (hereinafter, ASI) are used in the study. The Ministry of Statistics and Programme Implementation (MoSPI), Government of India (GoI) publishes a wide range of macro and industry-level data. All the data used in this paper has been collected from this source. We use wholesale price index (WPI) data from the Ministry of Commerce and Trade to deflate the industry-levelnominal gross value added to obtain real gross value-added data. In addition, the Labour Bureau's Consumer Price Index-Industrial Worker (CPI-IW) data is used to convert the nominal wage to real wage.The total number of employees at an industry level is considered employment in the present study. We use an panel of 38 years from 1981 to 2019. The key reason for selecting thisperiod is the data availability from these sources. The variables are explained in detail in Table 2.

Table 2: Variables Descriptions

Variables	Descriptions	*Apriori* sign
Labour Productivity	Gross Value Added Per Unit of Labour	Dependent Variables
Real Wage	Inflation-Adjusted Nominal Wage	Positive
Employment	The total amount of Man-days work	Mixed

Source: ASI (1980-81 to 2018-19)

5. Empirical Results

In literature, strong associations between labour productivity and real wages, as well as labour productivity and employment levels within the manufacturing sector, are well-documented. This section of the study aims to empirically investigate whether these relationships have persisted within the context of the manufacturing sector in Odisha from 1980-81 to 2018-19. Prior to conducting empirical research, it is essential to provide a comprehensive summary of the descriptive statistics for all relevant variables. Table 3 of the study evaluates the summary statistics of all the variables in Odisha's manufacturing sector. To ensure comparability, all variables have been converted into logarithmic forms, providing a consistent basis for analysis.According to the table below, the mean of total employment is 6.76, greater than labour productivity (-3.08) and real wage (1.63). Labour productivity had a higher standard deviation (2.15) than real wage and employment, which were determined to be 1.84 and 1.63, respectively. Table 3 has all of the sample's comprehensive statistics.

Table3: Summary Statistics

Variables*	Observations	Mean	Std. Dev.	Min	Max
Labour Productivity	615	-3.08	2.15	-10.55	5.06
Real Wage	615	1.63	1.84	-4.423	6.24
Employment	615	6.76	1.63	0.69	11.05

Source: Authors' calculation

Note: * All variables are in real terms.

Before analyzing the empirical results, it is necessary to conduct unit root and cross-sectional dependence tests, as they establish the foundation for robust econometric analysis. The unit root test evaluates the null hypothesis that the variables contain a unit root, signifying non-stationarity. If the null hypothesis is rejected, the variables are deemed stationary and suitable for analysis; otherwise, non-stationary variables require transformation, typically through differencing. On the other hand, the cross-sectional dependence test examines whether variables across different units are interdependent by testing the null hypothesis of no cross-sectional dependence. Rejection of this null hypothesis indicates the presence of cross-sectional dependence among the cross-sectional units which is industries in this case. The rejection of the null hypothesis in the unit root test confirms the stationarity of variables, whereas rejection in the cross-sectional dependence test identifies interdependencies. The results, shown in Tables 4 and 5, guide the choice of econometric techniques to ensure precise and credible analysis.

Table 4: Panel Unit Root Test Results

Variables	I (0)	I (1)
Labour Productivity	0.96	-13.97***
Employment	0.09	-11.40***
Real Wage	-4.91***	-14.56***

Source: Authors' calculation

Notes: *** indicates 1%, ** 5% and * 10% significance level.

In econometrics analysis, there are numerous tests to check for the presence of stationarity in a series. Taking into consideration the sample size and the asymptotic properties of the four tests: The Levin-Lin-Chu test (Levin et al., 2002), the Breitung test (Breitung, 2000; Breitung and Das, 2005), the Im-Pesaran- Shin test (Im et al., 2003), and the Fisher-ADF (Choi, 2002) tests which have as the null hypothesis that all the panels contain a unit root and the Hadri (2000) Lagrange multiplier (LM) test, which has as the null hypothesis that all the panels are stationary. Studies reveal that labour productivity and employment are stationary at the first difference, whereas real wages are stationary at the level.However, for the sake of simplicity, we have presented the unit root test results of the Levin-Lin-Chu test. As a result, we end up with variables that are a combination of I(0) and I(1) order. Given this intersection of

I(0) and I(1) order, the panel ARDL model is the most appropriate and preferable to investigate the long-run relationship.

Table 5: Cross-sectional Dependence Test

Variables	Breusch-Pagan LM	Pesaran scaled LM	Bias-corrected scaled LM	Pesaran CD
Labour Productivity	692.75***	33.76***	33.53***	14.99***
Employment	1035.65***	54.549***	54.32***	-3.33***
Real Wage	1445.53***	79.40***	79.178***	24.89***

Source: Authors' calculation

Notes: *** indicates 1%, ** 5% and * 10% significance level.

The Cross-sectional Dependence (CD) test is based on the average of the pair correction coefficients of OLS residuals regressions that test the null hypothesis of the presence of cross-sectional dependence. Table 5 of the study narrates the results of all four types of the CD test. All four tests signify the presence of cross-sectional dependence among the variables. It can be observed from the above Table 5 that all four models are statistically significant at one per cent. It also can be noted that the Bresusch – Pagan (1980) LM test and Pesaran (2004) scaled test can be used when T > N, whereas the Pesaran CD test is applicable when N > T. In this case, we will go with the Bresusch – Pagan (1980) LM test and Pesaran (2004) scaled test as we have many periods compared to its cross-section unit. Based on the above information, the following section discusses the empirical analysis of the Panel ARDL model.

Table 6: Panel ARDL Results

A. Long-Run Analysis

Variables	Coefficient
Real Wage	0.0198 ***(0.0034)
Employment	-0.0013***(0.0002)

B. Short-Run Analysis

Variables	Coefficient
ECT	- 0.3904 ***(0.0540)
Real Wage	-0.0839(0.1994)

Employment	-0.0678(0.0673)
Constant	-0.0553**(0.0257)
Log-Likelihood	- 609.094
Observations	615

Source: Authors' calculation from Panel ARDL Model

Notes: *** indicates 1%, ** 5% and * 10% significance level.

Based on the unit root test results, the ARDL Pooled Mean Group (PMG) Model was used to analyse the relationship between labour productivity, real wages, and the total number of employed people. Panel ARDL (PMG) provides the coefficient of results, which is homogenous in the long run but not in the short term. The dynamic link between the three factors varies significantly among the manufacturing sectors (Pesaran et al., 1999). As a result, this study has been carried out to examine the above. Table 6 shows the results of the Panel ARDL model. The most optimal panel ARDL lag length (1, 1, 1) was chosen for this estimation using the Akaike Information Criterion (AIC). The empirical study shows that the real wage positively and significantly affects labour productivity. A 1 per cent rise in real wages results in a 0.2 per cent increase in labour productivity. According to the findings, increased real income incentivises and motivates workers to work harder and more productively. As a result, we have established a positive and substantial association between these two variables. Again, higher real wages are connected with higher job opportunity costs, which pushes workers to work efficiently and productively. Furthermore, an increase in real wages raises the unit cost of labour, forcing companies to substitute capital for labour and increasing labour's marginal productivity. Existing research on labour productivity and real wage supports this empirical result (Fallahi et al., 2010).

On the other hand, as demonstrated in Table 6, employment level has an inverse relationship with labour productivity. Each percentage increase in employment results in a 0.001 percentage drop in labour productivity. The effect of employment on labour productivity is negligible. The inverse link between employment and labour productivity indicates the presence of the marginal productivity theory of labour. The more the labour presence in a unit, the lower the marginal productivity, and vice versa. Our findings support the existence of the marginal productivity theory of labour. Furthermore, the empirical findings are consistent with existing empirical research on labour productivity and employment. Research on labour productivity and employment also reports similar findings (Samargandi, 2018).

In addition to the long-run association, the ARDL model also examines the short-run association among the variables, as shown in the second part of Table 6. From our empirical study, it has been evident that both variables have not affected labour productivity in the short run. Table 6 does not show any significant relationship between the variables in the short run. In other words, real wages and levels of employment do not have any role in affecting labour productivity in the short run. Another fundamental property of the ARDL model is the estimation of the error correction term along with the short-run analysis. The ECM was estimated in this scenario as well. The primary goal of developing this method is to determine the long-run convergence of the variables from the short-run. Ideally, the ECT parameter should be considerably negative and significant (Akinlo & Olayiwola, 2021). All estimations have a negative and statistically significant ECT. A negative and significant ECT value indicates the long-run convergence of labour productivity, real wage, and employment level.

5.1. Robustness Analysis

To enhance our empirical resultsabout the association between labour productivity, real wage, and employment level, we furthered the study by constructing labour productivity using a new and different proxy for labour. To calculate the firm's labour productivity, we used the total number of man-days worked by each employee in our primarymodel. However, in our robustness analysis, we used a different proxy known as the total person engaged by the firm to calculate labour productivity (Rath, 2018). These variables were also obtained directly from the ASI. All other variables and models utilised in the analysis remain unchanged. Using a different labour proxy to calculate labour productivity allows us to examine whether comparable results hold. It also helps us to see if there is a substantial difference in the empirical results if we choose a different proxy to represent labour. In Table 7, a thorough summary of the robustness results is provided. Even though the coefficient differs from the primarymodel, we obtain identical findings. In the long run, the firm's real wages affect labour productivity favourably, whereas the level of employment has the opposite effect. Similarly, the research found no relationships between these factors in the short term. Again, the results from the ECM also find evidence of convergence in the long run. The findings remain the same if we use a different labour proxy. Therefore, we infer that labour productivity is positively influenced by real wages and negatively influenced by the level of employment in Odisha's manufacturing sector.

Table 7: Robustness Analysis

A. Long-Run Analysis

Variables	Coefficient
Real Wage	0.0112 ***(0.0123)
Employment	-0.0001***(0.0012)

B. Short-Run Analysis

Variables	Coefficient
ECM	- 0.1267 ***(0.0318)
Real Wage	0.0674(0.0121)
Employment	-0.0003(0.0346)
Constant	-0.0413**(0.0381)
Log-Likelihood	-516.0312
Observations	615

Source: Author's calculation from Panel ARDL Model

Note(s) *** indicates 1%, ** 5% and * 10% significance level.

6. Conclusions and Policy Suggestions

The examination of the linkage between labour productivity, employment, and real wages of Odisha's manufacturing sector is imperative from policy perspective point of view. Although a plethora of studies have examined this issue both cross-country and within a country across regions, however, to the best of our knowledge, none of the earlier studies have attempted to investigate this research issue in the case of Odisha. We have used annual data comprising 17 manufacturing industries of Odisha from 1980-81 to 2019-20. The study used both panel ARDL and panel ECM techniques to assess the effect of employment and real wages on labour productivity in long run as well as in short run.

First, we found a long-run relationship between labour productivity, real wages and employment. Second, real wages affect labour productivity positively in the long run, but the effect of employment on labour productivity seems to be negative. Third, employment and real wage did not affect labour productivity in the short run. This implies that the nexus between these variables is more significant in the long than the short run.

From a policy perspective, various manufacturing industries in Odisha need to promote the real wages of their workers, which would boost labour productivity in the long run. Higher labour productivity in the manufacturing sector leads to the output growth of these industries and creates more demand for labour inputs. The increase in labour demand generates more employment in the long run. Thus, to generate more employment at the industry level in the long run, the senior personnel and decision-makers at the industry level must facilitate better wage incentive policies in the short run.

In addition to its novel findings, this study acknowledges specific limitations. Firstly, the 38-year span of panel data may introduce structural breaks, potentially impacting the findings if these breaks are considered. Secondly, the analysis aggregates all manufacturing industries without distinguishing between labour-intensive and capital-intensive sectors. Differentiating these industries based on their technical intensity may yield varying results. Incorporating these limitations into the analysis could significantly alter the study's primary findings. So, addressing these limitations in future research may provide a more nuanced understanding of the relationships between labour productivity, real wages, and employment levels with in Odisha's manufacturing sector.

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Appendix-1

A.1. National Industrial Classification (2008) of Industry

10 – Manufacture of food products; 11 - Manufacture of beverages; 12 - Manufacture of tobacco products; 13 - Manufacture of textiles; 14 - Manufacture of wearing apparel; 15 - Manufacture of leather and related products; 16 - Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials; 17 - Manufacture of paper and paper products; 18 - Printing and reproduction of recorded media (this division excludes publishing activities; see section J for publishing activities; 19 - Manufacture of coke and refined petroleum products; 20 - Manufacture of chemicals and chemical products; 21 - Manufacture of pharmaceuticals, medicinal chemicals and botanical products; 22 - Manufacture of rubber and plastic products; 23 - Manufacture of other non-metallic mineral products; 24 - Manufacture of basic metals; 25 - Manufacture of fabricated metal products, except machinery and equipment; 26 - Manufacture of computer, electronic and optical products; 27 - Manufacture of electrical equipment; 28 - Manufacture of machinery and equipment; 29 - Manufacture of motor vehicles, trailers and semi-trailers; 30 - Manufacture of other transport equipment; 31 - Manufacture of furniture; and 32 - Other manufacturing.

Article

Evolution of Intermediary-led Seasonal Labour Migration to Brick Kilns in Bolangir, Odisha

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Abstract

Labour migration from the rain-fed areas to brick kilns during the agricultural off-season to earn a livelihood has become common in India. Uneven regional development, natural resource degradation, dispossession, social exclusion and lack of assets at the source are the leading causes of seasonal migrations. The present study examines and analyses the emergence of seasonal migrations in the backdrop of the prevailing economic and socio-cultural dimensions of the local economies by taking labour migration from Odisha to the brick kilns of other states. Like other seasonal migrations of the poor and less educated workers, the intermediaries, locally known as 'sardars', also facilitate migration from the study area. The study finds that the seasonal migration of labourers from this area to the brick kilns has a long history. Dalit households started it to escape poverty, starvation, and social exclusion. Over time, informal institutions that facilitate migration and formal ones that prevent labour exploitation have evolved around the phenomenon. However, the complex interactions of these institutions have failed to protect the labourers from exploitation. The paper suggests the need for migration-supportive institutions to facilitate labourers' movement with their identity and dignity intact.

Keywords: Seasonal migration, Migrant labourers, Bbrick kiln, Labour sending mechanism.

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Introduction

Labour migration from the rain-fed areas of states like Bihar, Jharkhand, Odisha, and Uttar Pradesh to the brick kilns of other states such as Andhra Pradesh, Telangana, Tamil Nadu, Karnataka, and Delhi during the agricultural off-season to earn a livelihood has become a common feature in India (Rogaly et al.,2001; Mosse et al.,2002; Ghosh,2009). Such labour movements are also noticed in neighbouring countries like Pakistan, Nepal, Afghanistan, and Bangladesh (Upadhaya,2004;Ercelawn & Nauman,2004; Croitoru & Saraf, 2012). Theories like the Sustainable Livelihood Framework of Migration, New Economics of Labour Migration and Structural Theory of Migration have been developed by researchers to explain the movement of labourers seasonally. Uneven regional development, natural resource degradation, and dispossession due to the alienation of rights over the commons are the causes of such migrations (Ambagudia, 2010; Mishra, 2016). Attempts are also made to show poor households' labour deputation strategies to avoid starvation in the short run and to accumulate assets in the long run (Deshingkar & Start, 2003). The relatively less poor households often depute some members with their neighbours to meet the exigencies, which are categorised as coping strategies (Haberfeld et al., 1999). People of low castes and women often migrate to escape the socio-cultural restrictions (Shah, 2006). Caste, representing the household's socio-economic and cultural dynamics, is an important determinant of seasonal migration,according to Nag et al. (2023).

Recently, researchers have adopted the Gramscian approach to analyse the motive and impact of seasonal migration (Rai, 2018; 2022; Shah & Lerche, 2020). As the Dalits and Adivasis experience structural oppression in their native place, they migrate and accept the exploitation in their workplaces (Shah, Lerche, 2020). Rai (2018 and 2022) finds a change in social dynamics through seasonal migration. Counter-hegemonic ripples are noticed in his studies when the returnee migrants with new ideas and confidence start challenging the prevailing caste and class hegemony. However, none of these studies have attempted to examine the emergence of these seasonal migrations against the backdrop of the prevailing economic and socio-cultural dimensions of the local economies. Here, an attempt has been made to analyse this by taking labour migration from Odisha to the brick kilns of other states, though initially, such migration was only intra-state.

Every year in the lean period, lakhs of people from the KBK (undivided Kalahandi-

Balangir-Koraput districts) region of Odisha migrate to peri-urban areas of Andhra Pradesh, Tamil Nadu and Karnataka to work in the brick kilns (Meher, 2019; Banoo & Das, 2023). High concentration of marginalised sections like Scheduled Tribes (STs) and Scheduled Castes (SCs)[1] (50.6 per cent and 20 per cent, respectively), the prevalence of high poverty and deprivation, low human development and high multidimensional poverty are the important features of this region (Naik & D'souza, 2021; NITI Aayog, 2021[2]).

In this region, inadequate livelihood opportunities in the agricultural lean season and low earnings from agriculture force many small and marginal farmers and landless agricultural labourers to migrate to other places for work, earn and survive (Mishra, 2011). Workers' migration to brick kilns from this region is primarily distress-driven (Mishra, 2016; Banoo & Das, 2023). SCs and STs are predominant among these migrants (Mishra, 2020). SC households, mainly landless labourers, endure intense difficulties and use migration as a survival strategy (Sengupta & Vijay, 2015; Mishra, 2016). The STs migrate to brick kilns because their traditional occupations of cultivating and collecting forest products are under mounting pressure due to the government's forest policies and development projects (Ambagudia, 2010). Brick kiln migration from this area is viewed as a structural issue rooted in the historical process of development of the economy and dispossession of the traditional rights of the people over the commons, causing their marginalisation and deprivation (Mishra, 2020).

Migration to brick kilns is also facilitated by intermediaries, locally known as 'Sardars' (KARMI, 2014; Sengupta & Vijay, 2015). A Sardar provides an advance to these labourers and binds them with a contract to work in the brick kilns for several months. He is funded by the employer and is tasked with making travel arrangements for these migrants and for enforcing the contract. Studies reveal that migrant workers face harassment in several places during their journey and at their destination (Koy Thomson et al., 2005; Das et al., 2021). Employers and Sardars exploit these workers and earn huge profits from this system of debt-bondageled migration (Breman, 1996; Chhatray, 2011; Das & Seth, 2014).

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[1] They are constitutionally recognised groups of people in India who have been historically disadvantaged and marginalised to give them certain protection.

[2] https://odishatv.in/news/exclusive/niti-mpi-shows-odisha-s-kbk-syndrome-lingers-on-from-narashima-rao-to-naveen-patnaik—164926

Objectives, Data and Methodology

This study examines the emergence of seasonal migration to brick kilns from the KBK region and the supporting institutions promoting it. We have selected Balangir district as the site of our study, as seasonal migration has long been present in this region (Bhuyan & Das, 2022). A large number of labourers migrate from this district during the agricultural off-season[3]. There are six migration-prone blocks in this district[4]. We visited the District Labour Office, Balangir and the important railway stations of the district to acquire information about the routes, local Sardars and other data relevant to the study. A preliminary visit to five migration-prone blocks was made, which revealed that migration to the brick kiln started from the Belpada block in Balangir district in the 1950s. Our investigations revealed that, in the 1950s, many households struggled to get even one full meal a day. People reported that through migration, they could escape starvation and death. Thus, to explore the history of seasonal migration from this area, the Belpada block was selected purposively. Another block (namely, Turekela) was randomly selected from the other five blocks of Balangir district to understand how and why people from other blocks started migrating in the off-season.

After discussing with the employees of the block offices, a list of migration-prone villages was prepared. Using simple random sampling, eight villages were selected from the list[5]. Afterwards, a visit to the Anganwadi centers of these villages was made to collect data such as the total number of households, their caste composition, and migration status. Simple random sampling was used to select migrant households from each category. Accordingly, 158 migrant households were interviewed from June to September 2022[6]. Before the household survey, focus group discussions were conducted to understand the history, causes and process of seasonal migration from the sample villages. From the selected blocks, 40 Sardars and 50 assistants of Sardars were also interviewed to understand the evolution of different mechanisms for smoothening the process of labour deputation by these intermediaries. Care has

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3 *The New Indian Express* (2023): "40,088 labourers migrated from Odisha, says Minister Sarada Prasad Nayak" , Available at https://www.newindianexpress.com/states/odisha/2023/Nov/24/40088-labourers-migrated-from-odisha-says-ministersarada-prasad-nayak-2635790.html

4 https://balangir.odisha.gov.in/sites/default/files/2023-05/2019111476.pdf.

5 Four from each block to capture village specific socio-economic and cultural diversity.

6 Selected 160 households but data on two households were found not suitable for the study.

been taken to include Sardars from various places to comprehend the historical context of this migration. Some pioneering Sardars' friends and relatives were also interviewed to gather information[7]. We have also interviewed twelve employees of the railway stations in Kantabanji, Titalagarh, and Harisankar Road, which were identified as the main stations through which labourers move to neighbouring states to work in the brick kilns.

The study adopts qualitative analysis based on oral narratives due to the limited availability of secondary data on migration history and the key role of intermediaries.

Findings

The findings of this study are presented in two sections. The first section describes the evolution of seasonal migration from the area and the migration history of sample households. The second section discusses the evolution of different institutions and the mechanisms developed by intermediaries for smooth labour deployment. This is followed by a brief discussion of the government policies to prevent the exploitation of migrants and their violations, which shows the need for a supportive, labour-friendly policy.

History of Migration to Brick Kilns from Balangir District

Odisha's poverty, inequality and social deprivation have their roots in the colonial land revenue administration and land management, unfavourable forest policies, climate disasters, and caste exclusivity (Bailey, 1975; Baboo, 1988; Pandey, 1995; de Haan & Dubey, 2005; Mishra, 2020). Odisha remained trapped in a consistently low agricultural productivity cycle due to a lack of investment in land development and technology (Mishra, 2009). The destruction of local small-scale and cottage industries resulted in overcrowding in agriculture and meagre wage rates for workers. Forest policies of the 1860s brought the forests under the government's control and deprived the neighbourhood tribals of their livelihood (Pattnaik, 2017). Frequent occurrences

[7] Dashrath Suna of Harijanapada, of Belpada Block is said to be the first person from this district who migrated to work in the brick kiln. Later on he started labour deputation. In course of time when it became a lucrative earning source Bablu Pathan of Kantabanji started large scale labour deputation from this area. Bablu was known to be the Baron of labour deputati
on.

of floods, droughts, famines, and isolation of local economies due to the underdeveloped transportation facilities led to a large number of starvation deaths (Das, 1989 Samal, 2000; Ambagudia, 2010) and a high level of poverty in the rural areas of the state.

We assume that the caste hierarchy restricts access to resources and occupational choices, resulting in segregation and social exclusion. After independence, government initiatives were made to improve the situation, but the effect was trivial (Dushkin, 1967). Thus, the rural economy of Odisha in the 1950s was characterised by high levels of socially differentiated poverty[8]. Balangir district was not an exception. While discussing the history of migration to brick kilns from Balangir district with some old Sardars, senior residents and the son of Dashrath Suna, we came to know the existence of acute poverty among the Dalits of the area. In the 1950s, landlessness and caste barriers to various occupations forced them to remain mostly half-starved during the lean season. People from ST communities were slightly better off due to their access to forest-based livelihoods. The upper caste Hindus with large landholdings were the well-off households of that time; most were *Gountias* or village heads. The other lower caste Hindus presently coming under the Other Backward Castes (OBCs) had their position below the upper castes but above the Dalits and Adivasis. In this scenario, the Dalits desperately needed a new livelihood opportunity. In 1955, the creation of the South-Eastern Railway, which passed through this area[9] had a station at Kantabanji, 80 km from Balangir town, creatingan opportunity for them. There was a massive demand for clay-fired bricks. Dashrath Suna, a person of this locality, got the opportunity to be a "saviour" for the people of this area. This paper includes a detailed narration of the events obtained from the interviews with his son, a few Sardars, senior railway employees of the area, and the labourers who have been migrating to brick kilns with their parents since childhood.

[8] Macro data on caste, class and power distribution in Odisha especially up to nineteen seventy is absent (Pathy,1981). Pati (2019) dwelling on rich archival and ethnographic materials depicts the marginalisation of Adivasis and Dalits during 1800 to 1950. In the fifties no radical positive intervention in favour of these marginalised section was taken by the Government. Orissa Scheduled Areas transfer of immovable property regulation was enforced only in 1959 (Govt. of India,1960-61: 416). Land Reforms Act, 1960 to impose Land Ceiling was implemented in Odisha with laxity. Drawing on the works of some Sociologists, Pathy (1981) finds the continuity of the caste wise class position in Odisha even in 1970s. Based on these studies the authors infer the existence of socially differentiated poverty in Odisha. The situation of Balangir district was conceived from the oral narratives of the near relatives (son), and contemporaries of Dasrath Suna, the first migrant from Balangir district who belonged to Dalit Community.

[9] It was carved out from the then Eastern Railway

Dashrath Suna: The First Worker-labour Supplier from Balangir

"Dashrath Suna was from Harijanpada of Belpada village, Belpada block[10] and belonged to the *Gonda (or Gana)* caste, whose traditional occupation is cleaning drains, toilet tanks, etc. He and most of his fellow villagers were suffering from acute poverty and starvation in the agricultural off-season. Occasionally, they were getting wage employment for land digging and road construction by the local *Gountia*[11]. Dashratha had learnt the technique of brick-making from his father-in-law. He got an offer from a contractor to make bricks for the construction work of the Kantabanji railway station. In 1956-57, he took his wife and some other people from his village to Kantabanji, taught them the skill of brick making and produced the bricks for the contractor. Thus, the migration of workers for brick kilns started in Balangir, though it was an intra-district migration. During the initial days of migration, the workers received only food for that work, which seemed like a boon to avoid starvation." Son of Dashrath Suna (aged 48 years).

According to Sindhu (aged 67 years) and Vikram (aged 72 years) Sardars, the skill, sincerity, and hard work of Dashrath Suna and his team attracted the attention of other contractors, and they received offers from different places. One such offer was made by Kalu Charan Panigrahi and Niranjan Panda to mould bricks for the kilns in the Hinjlikato village of Ganjam district. This way, inter-district migration from Belpada began with twenty people. They worked in the kiln for eight months and returned to Belpada in the rainy season. They were not given any wages for that; instead, they received meals, which was acceptable because they lacked any other earning opportunity to buy food for themselves. By managing food during the lean season, these families were considered economically better off than the rest of the population in their locality. Such information was also obtained from some Sardars who were contemporaries and relatives of Dashrath.They said that over time, when demand for bricks increased in the state, kiln owners offered Dashrath some financial incentives over and above the travel cost of labourers. People of Belpada and its neighbourhood, especially the Dalits, also requested Dashrath to take them with him as brick kiln workers. So, he became a labourer-cum-labour-supplier.

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[10] Harijan implies scheduled caste; the hamlet was mainly domiciled by the SCs.

[11] Generally, he is the person who has the maximum control over the village economy with the largest land holding, usually practicing money-lending.

The severe crop failure of 1965 in western Odisha not only increased the volume of migrants to brick kilns but also brought a significant change in the social composition of migrants (Panda, 2017). People of the ST and OBC communities also approached Dashrath for an opportunity to go with him to the brick kilns to survive the shock. Dashrath acquiesced and grew in both economic and social status.

Over time, Dashrath stopped working as a labourer in the brick kiln and undertook the task of deputation and management of labourers and acquired the status of the first 'Labour Sardar' in the locality. Good earnings from labour deputation attracted some enterprising young men into this profession. However, they struggled in the business because of a lack of contact with kiln owners and hold over a sizable number of labourers. They requested that Dashrath employ them as his assistants. He accepted the proposal, hoping to manage more workers and gain a higher status. After a few years, he designated them as Second Sardars to send more labourers to distant places.

Visakhapatnam, a town in Andhra Pradesh, experienced rapid urbanisation in the late sixties and early seventies. Fuelled by the growth, the number of brick kilns increased, and kiln owners requested Dashrath to send labour for brick moulding as he had become a well-known Sardar in Ganjam, the border district of Odisha and Andhra Pradesh. This led to inter-state labour migration to the brick kilns of Andhra Pradesh from Balangir. Subsequently, some of the Second Sardars developed connections with the kiln owners while managing the labourers to earn a higher income. They became the new Labour Sardar, leaving the team of Dashrath. A case study of one such Second Sardar is given in Box I. Over time, with the rise in kilns, the number of migrant workers, Sardars and Second Sardars increased in the district.

Box I: Rise of Mantu as a Labour Sardar[12](original name changed)

Finding labour deputation a lucrative activity, Mantu Pathan tried to enter it. He approached Dashrath, acted as his assistant, and became a Second Sardar. Over time, after developing contact with the kiln owners and connectivity with the labourers, he left Dashrath and operated independently. As an enterprising businessman, he also developed a rapport with the South Indian railway employees of Kantabanji station. Through them, he could forge connections with the kiln owners of South Indian states for labour deputation.

[12] This description is based on the discussion with one of the relatives of Mantu who once acted as an assistant of Mantu and now is acting as an important Sardar of Kantabanji and other Sardars as well as with some railway employees. His age at the time of interview was around 65 years.

The introduction of an advance payment system to the labourers helped Mantu to have more control over the workers, who, instead of borrowing from the moneylenders at a monthly interest rate, took the advance from Mantu with a contract to be deputed by him for brick-making in the forthcoming brick-making season.

Meanwhile, he also learnt some South Indian languages to facilitate his operation in almost all the South Indian states. The extensive railway linkage between Odisha and these states helped his endeavour. Mantu Pathan became the most important Labour Sardar in Kantabanji in the last quarter of the twentieth century. Mantu has passed on, but his relatives have taken up his business and are prominent Sardars of the area.

Through a field visit,we learned that approximately 5000 Labour Sardars (including Second Sardars) were operating in the district. Some had started their career as brick kiln workers and became Second Sardars and, ultimately, Sardars. Their work experience, enterprising behaviour and risk-taking attitude helped them achieve vertical mobility. Some, like Mantu, had entered the operation as assistants to Sardar to understand the process and to gain connectivity with the kiln owners and the different labour movement regulating officials. It is also reported that some of the ambitious labour supervisors of the kilns, after working in the kiln for several years, started brick production. They contacted some Second Sardars (instead of the Sardars) to supply labourers to their kilns, who, accepting the offer, started deputing themselves to these new kiln owners to become Sardars.

This process resulted in an increase in the number of kilns and kiln owners at the destination and a rise in the number of Sardars at the origin.The above facts also indicate the rise in migrants from this area. Taking a conservative estimate of 50 workers deputed by one Sardar (supported by four Second Sardars), the number of workers deputed at any point in time comes to approximately 50,000 a year[13]. It was also found that to avoid conflict arising from the competition in labour deputation, Sardars have tacit agreements demarcating areas to themselves for labour deputation.

[13] We assume one Sardar has four Second Sardars to assist him; together they constitute one labour deputing unit and send on an average of 50 labourers. This way, we estimate 1000 labour dep uting units and 50,000 migrant workers

Migration History of the Sample Households and their Socio-economic Characteristics

While interviewing the sample households, it was found that out of the 158 sample households, 156 could tell us when their family members migrated for the first time. 8.33 per cent of the households reported that the migration history of their family dates back to the 1960s, 16 per cent reported that it was in the 1970s, and 20.51 per cent reported the 1980s. Block-wise figures are presented in Table 1, showing that migration volume has increased over time. Out of the two blocks, it was found that the people of Belpada have a longer history than those of Turekela. During our interview, some old people of the Belpada block also reported that some families in their villages started migrating in the 1950s.

Table 1: Migration History of the Sample Households across Blocks

Starting of migration	Belpada		Turekela		Combined	
	Number	%	Number	%	Number	%
1960s	12	14.8	1	1.3	13	8.33
1970s	22	27.2	3	4	25	16.03
1980s	18	22.2	14	18.7	32	20.51
1990s	16	19.8	18	24	34	21.79
2000 to 2009	11	13.6	14	18.7	25	16.03
2010 and onwards	2	2.5	25	33.3	27	17.31
Total	81	100	75	100	156	100

Source: Household survey of sample villages from June to September 2022

The analysis of social category-wise sample households' migration history reveals that up to the 1970s, only Dalits were migrating. The migration of the ST households is visible only in the 1980s. The OBCs joined the flow in the 1990s but became more apparent after 2000 (Table 2).

Table 2: Social Category-wise Migration History of Sample Households

Starting migration in	ST		SC		OBC	
	Number	%	Number	%	Number	%
1960s			13	14.4		
1970s	2	4.76	23	25.5		
1980s	5	11.9	27	30		
1990s	11	26.19	20	22.2	3	12.5
2000 to 2009	11	26.19	3	3.3	11	45.8
2010 and onwards	13	30.95	4	4.4	10	41.7
Total	42	100	90	100	24	100

Source: Household survey from sample villages from June to September 2022.

Note: *No information is available for two ST sample migrant households.

While pondering over the reasons that motivated/forced people to join the migration flow, it was found that 27 per cent opted for migration to avoid starvation. As high as 39.2 per cent of households started migrating to ensure food and other basic needs for the year, which we have categorised as the 'survival strategy'. Around 14.6 per cent of households started migration to repay their debt. For SC households, starvation was an important reason for migration. The ST households reported that debt repayment was their primary reason for migrating. As much as 79 per cent of the OBC households said migration was their survival strategy (Table 3).

Table 3: Major Reasons for (First-Time) Migration of Households across Social Categories

	Combined		ST		SC		OBC	
Causes	Number	%	Number	%	Number	%	Number	%
To avoid starvation (Regular)	43	27.2	6	13.64	36	40.00	1	4.17
To avoid starvation (Occasional)	30	19	5	11.36	25	27.78	0	0.00
Survival (Support for the year)	62	39.2	14	31.82	29	32.22	19	79.17
Debt repayment	23	14.6	19	43.18	0	0	4	16.67
Total	158	100	44	100	90	100	24	100

Source: Household survey from sample villages from June to September 2022

Evolution of Institutional Arrangements for Labour Deputation

Regular deputation of labourers to the brick kilns of other states in the country requires an institutional arrangement. The system started as a simple structure where the kiln owners directly interacted with the labourers, like Dashrath Suna and his associates. The team members had more economic and demographic homogeneity. They were given food, transport costs (paid in advance), and temporary shelters near the place of work during their stay. Subsequently, the structural setup of the labour-sending mechanism changed. The rise in demand for brick moulding made Dashrath a labourer-cum-labour-supplier to the kilns, who received some payment from the kiln owners as an incentive for bringing skilled and hard-working people with him for brick moulding. He gained the right to select a member for his team and could pressurise the employers for his incentives since the latter depended on him to reduce their search costs. Over time, the leader pressed for wages for the workers in addition to providing food, shelter and transportation.

With years of experience and earnings, Dashrath became a labour supplier, an intermediary between the labourers and the employer, locally known as the 'Labour Sardar'. He received payment for the number of labourers he deputed, and therefore, he also deputed labourers seeking work from other communities to increase the number of workers under him. Later, with the rise in migrants, assistants to Sardars and Second Sardars were created to smoothen the migration process. Further, a couple of informal arrangements were devised by the Sardars and the employers to ease the migration flow. The introduction of an advance payment system was one such arrangement.

Through the Sardars, the employers paid the labourers an advance (in cash) to bind them for the forthcoming season. The timing of the advance payment was from September to October, when the labourers faced food and income insecurity. In this period, an important festival – 'Nuakhai' is celebrated in the region, and the advance is spent on that purpose. As per the field data, the "advance system" was introduced in the studied villages in the 1960s. The initial advance payment was INR 100 to INR 200 per family, depending on the number of workers from the family. At the destination, the workers received weekly wages for food and other essentials known as '*Kheri*'. The piece rate of brick moulding was 25 paise per 1000 bricks then; hence, at the end of the season, payments were made to the labourers after deducting the advance and the sum of the weekly wage payments. The advance payment system increased the responsibility of the Sardars to minimise the cases of defaulters (labourers who did not migrate after taking the advance). Sardars appointed Second Sardars and Assistants to ensure labour accountability and enforcement of the contract.

Different studies have also reported that the Sardars and employers exploited the labourers. Long hours of hard work, few leaves even on medical grounds, sub-human conditions of living at the destination, and poor treatment during transportation were reported. Such reports indicated the need for government intervention, resulting in the Contract Labour (Regulation and Abolition) Act, 1970 and the Orissa Contract Labour (Regulation and Abolition) Rules, 1975, which further led to the passing of Inter-State Migrant Workmen (Regulation of Employment and Condition of Service) Act, 1979 (ISMW Act, 1979). The ISWM Act, 1979 provides detailed provisions for the protection of migrant labourers through mandatory registration of the contractor, registration of the employee's work unit, maintenance of all records relating to the whereabouts of labourers, employer, amount of advance given, period of work, wage rate, etc., by the contractor. These Acts increased the risks and costs of the Sardars and the kiln owners, who tried to escape some restrictive clauses to keep their profits high. Measures adopted by them include sending more workers than their licensed count, showing more advance payment than the actual, using different routes/ means/ timing of transportation of labour from the locality, and giving commissions to regulatory personnel (Das & Seth, 2014; Daneil, 2014; Sengupta & Vijay, 2015).

Intermediary-mediated labour migration through advances strengthened the informal credit market in the area. Usually, the poor borrow from local moneylenders during their bad days. Lenders avoided lending when the default payment possibility was high. The advance payment system for future migration created some creditworthiness for such households. The local moneylenders were assured of repayment from the advance to be received by the borrowing migrant family. Such access to informal credit led to a vicious circle of debt-bondage led migration for the people of this area. Households resorted to massive borrowing for various purposes, including socio-cultural rituals, to assert their social identity, forcing them to migrate.

Present Scenario

Our frequent visits to the field helped us to understand and get information related to the present system of advance payment, the borrowing-advance inter-linkages, and the structural arrangements by the Sardars for facilitating migration. It was observed that the basis of the advance system has been modified, and the advance amount has been increased over time. Earlier, the basis of advancement was family, and it was recorded against the male working member. After 2010, advance payments were made to each working family member. In the year 2022-23, per head advance was found to be in the range of INR 30,000 to 50,000, depending on the destination and the duration of the stay of the workers. The workers decide the advance amount and the Sardar decides the place of work depending upon the demand from the employers. Workers seeking INR 50,000 were deputed from the end of September or the beginning of October to Hyderabad. Workers seeking INR 40,000 were sent to Chennai, Tirupati, Bengaluru or Visakhapatnam, and they were sent from the end of October or the beginning of November. Workers opting for INR 30,000 were sent to the places mentioned above from the end of November to the beginning of December. It was found that in 2022-23, on average, a migrant household was getting INR one lakh as advance, a lucrative sum for a labour household in the locality.

It was found that more than 90 per cent of the households had debt. The average amount of borrowing was as high as INR 1.3 lakhs, and the average share of debt to the annual household income was 75 per cent. As high as 97 per cent of the households reported that they had borrowed money to spend on rituals and to meet daily expenses. Only one per cent of the households stated that they had borrowed to renovate their houses. None had reported that the borrowed amount was used for capital accumulation. Thus, migration has failed to create livelihood assets at the origin and perpetuated the vicious cycle of debt-bonded led migration.

It was found that the Sardars were engaging a variety of assistants. They even used government officials to get important information (like date, time and place of surprise checks) and local ward members to facilitate rule violations. Table 4 presents a detailed description of the structure of the workers in different hierarchies involved in the labour supply chain. Each Sardar had three to five Second Sardars and at least eight to ten Assistants (locally known as helpers)[16]. The Assistants were subdivided into different categories depending on the assignments. Sardars also possessed different vehicles, especially for transporting labourers from their villages and dropping them off at the railway station or bus stand. One or two Assistants bring the labourers from their homes to the railway station and hand them over to the assigned Assistant, who books tickets, arranges food for the labourers and ensures their boarding onto the train. The Second Sardar takes the labourers to their destination and hands them to the kiln owner. One Assistant accompanies the Second Sardar to the destination with these labourers.

Table 4: Roles and Responsibilities of Different Agents

Hierarchy/ Designation	Functions and Responsibilities
I. Sardar	Registers annually to send labourers to other states.
	Collects advance from brick kiln owner(s)
	Performs the paperwork and formalities of the labour movement in the District Labour Office
	Undertakes the overall supervision and execution of the labour delegation
	Attends the Court in case of any summons
	Negotiates with journalists, police, labour officials, etc.
II. Second Sardar	Accompanies labourers during their journey from the railway station to the destination
	He manages all the en-route problems relating to Railway Protection Force(RPF),Government Railway Police(GRP), railway employees, journalists, food arrangements for labourers, etc.
	Assists the Sardar in recruiting the sub-ordinate Assistants
	Supervises subordinates and Assistants and coordinates them.
	Hands over the labourers to the agents of the kiln owners at the destination
	Moves to the destination whenever any problem relating to the labourers arises
III. Assistant	Collects money from the Sardar and makes an advance payment to the labourers.
	Accompanies labourers to the railway station from their homes and hands them over to the assigned Assistant
	Books railway tickets for the labourers, receives the labourers at the station, remains with them until they board the train, and ensures their boarding.
	Accompanies the Second Sardar to assist when a large number of labourers are deputed to any destination
	Works as the driver while transporting labourers from villages

To avoid a competitive hike in advance, Sardars have made tacit agreements and divided the areas among themselves for labour deputation. They maintain cordial relations with the village heads and fund socio-cultural activities in their operational area. By this, they insulate themselves from people reporting their activities to the police or journalists. Cases of local people helping Sardars in enforcinga contract were also found. It was also reported that while deploying labourers by train, Sardars pay kickbacks to railway booking clerks, station masters, and the RPF to depute more people than their license permits. Some of the Second Sardars also reported that at the destination, the kiln owners make informal arrangements with the police, labour officers and journalists to avoid any raid at the kiln site. Thus, they violated labour laws and made the helpless workers accept exploitation as their destiny.

Conclusion

The study tried to explore the evolution of intermediary-led labour migration from Balangir district of Odisha and found that Dalit households started the migration phenomenon to escape poverty, starvation, and social exclusion. Eventually, poor households of other social groups, especially those belonging to the tribes and OBCs struggling for their life and livelihood in the locality, started migrating to brick kilns. Gradually, it emerged as an intermediary-led seasonal migration, facilitated by the growth of a couple of informal institutions, resulting in labour exploitation. This study can be linked to historical structuralism. The debt-bondage-led migration system has failed to create livelihood assets at the origin. To protect inter-state migrant workers from exploitation, legislations like the Orissa Dandan Labour (Control and Regulation) Act, 1975, and the ISWM Act, 1979, were passed.

From the study, it is learnt that while sending labourers to the destination, sardars are adopting different means to send more labourers than they are authorised to do. These actions put workers in danger and dehumanize them. State machineries are used to control the sardars. An individual should be able to migrate (within the nation) to make a living in a democracy, and it should be the duty of the state to facilitate this. To ensure workers' safety, the state can offer smart ID cards and the e-Shram portal for registration. Creating "Migrant Help-Desks" at the block and district levels to provide information, legal assistance, and a means of reporting and resolving problems will be of great help. At the beginning of the migration season, holding awareness programs to educate the labourers about their rights and the facilities available for them will reduce their risks and vulnerability. This will facilitate the movement of labourers with their identity and dignity intact.

One of the study's limitations is that, despite the region's more than 50-year history of seasonal movement, it did not examine how it affected the social caste-class fabric of the area. Efforts might be made for this in the future.

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Article

Socio-economic and Geographical Variation in Average Life Span in Odisha: Evidence from the Annual Health Survey

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Abstract

The life expectancy data in India is available by state, age, sex, and place of residence; estimates based on social and economic categories are still limited. This lack of disaggregated data makes it difficult to fully understand and address health inequalities across different population groups. Acknowledging this limitation, this paper analyses the social determinant of age at death in Odisha based on 65444 deceased individuals aged 15 and above from 2007-11 obtained in three rounds of Annual Health Survey data. Exploratory data analysis and multivariate OLS regression are applied to study the differences in age at death regarding regional and temporal attributes. While the coastal districts have a higher average lifespan, the southern districts have the lowest due to factors such as lower literacy rates, low monthly per-capita expenditure, a higher percentage of Scheduled Caste and Scheduled Tribe (SC/ST) population, higher levels of poverty, and poor access to healthcare.

Keywords: Life Expectancy, Socioeconomic Status, Annual Health Survey, Regional Disparity, Caste

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Introduction

Health is a fundamental determinant of individual well-being and encompasses multiple dimensions, with life expectancy being a prominent indicator of population health. Life expectancy is a proxy for overall health, reflecting the quality and duration of life. As a critical measure, it provides a comprehensive summary of mortality and offers insights into population health and longevity. The life expectancy of individuals is notably influenced by a range of socio-economic and demographic factors, which contribute to variations in longevity and result in disparities acrossdifferent populations. Countries use various strategies to enhance life expectancy, particularly in healthcare, education, and other social indicators. Over the past few decades, the average lifespan has extended as life expectancy has significantly increased. This improvement can be primarily attributed to heightened healthcare awareness and reduced mortality rates among infants and children. The concerted efforts in these areas have collectively contributed to extending life expectancy globally. The global life expectancy at birth has increased from 49.0 years in 1950 to 71.7 years in 2021 (Schumacher et al., 2024). The life expectancy at birth in India has experienced a substantial increase, rising from 49.7 years from 1970-1975 to 70.0 years from 2016-2020. This represents a gain of 20 years over the past four decades. During 2016-2020, life expectancy at birth was higher in urban areas (73.2 years) compared to rural areas (68.6 years). This marks a reduction in the gap between rural and urban life expectancy compared to 1970-1975 when life expectancy was 48.0 years in rural areas and 58.9 years in urban areas in India. In Odisha, the overall life expectancy for 2016-2020 is 70.3 years, with rural areas having a life expectancy of 69.8 years and urban regions having a life expectancy of 72.2 years. Additionally, female life expectancy at birth in Odisha is higher, at 71.4 years, compared to the male life expectancy of 69.1 years (ORGI, 2022).

Despite the dramatic increase in life expectancy, inequality in longevity persists, and in many countries, the gap in longevity has widened (Dahl et al., 2024). The rise in life expectancy inequality can be attributed to several factors. Socioeconomic status (SES) is a powerful determinant of life expectancy. Income, wealth, and education are broadly categorised as the SES. Higher SES often correlates with better access to healthcare, healthier diets, and safer living conditions. Conversely, lower SES is associated with higher stress levels, exposure to environmental toxins, increased risk of chronic diseases reduced lifespan and a higher incidence of diseases and mortality (Cutler et al., 2008; Glymour et al., 2014). There is the existence of a socioeconomic gradient in health, where the risk of mortality and morbidity is progressively reduced from lower to higher socioeconomic strata.

The differences in SES are not the only dimension in which inequality in health is structured; degrees of social stratification shape the health outcomes in a society. Dividing individuals into meaningful groups is a prerequisite for analysing socially patterned health longevity disparities, and each society has its way of dividing and stratifying people into different social groups. The difference between Whites and Aboriginals in Australia, race/ethnicity and nativity in the US, and level schooling in the UK, while caste has been central to studying the social division of people in India (Arcaya et al., 2015). SES includes income, wealth, and education and encompasses race, ethnicity, and individual rank in a stratified society. These intricacies of SES make it hard to distinguish their individual effects on health and longevity.

Asaria et al. (2019) found disparities in life expectancy based on wealth distribution in India, as the poorest fifth of households have lower life expectancy at birth than the wealthiest fifth of the household. Disparities exist in life expectancy at birth in India based on social group and religion (Kumari & Mohanty, 2020; Vyas et al., 2024; Siddiqui & Singh, 2022).

Besides SES, the access to quality healthcare that is preventive care, timely diagnosis and effective treatment can significantly expand lifespan. Ahmad et al. (2023) found that urbanisation and income inequality significantly negatively impact life expectancy, while health expenditure has a significant positive effect. Lifestyle choices, such as diet, physical activity, smoking, and alcohol consumption, have direct effects on life expectancy. Healthy behaviours can reduce the risk of diseases like diabetes, heart disease, and cancer, increasing life expectancy. A study based on 15 European countries revealed that the main factors contributing to the life expectancy gaps were smoking, low income, and high body weight (Mackenbach et al., 2019). Data from 16 high-income countries show a significant increase in life expectancy from 1850 to 2000, with females living longer than males. Differences in life expectancy among these countries have narrowed over time due to improved living standards, healthcare, and medical advancements (Bongaarts, 2006). Education is a significant determinant of life expectancy. Higher educational attainment is linked to better health outcomes and longer life. Educated individuals are likelier to engage in health-promoting behaviours and less likely to participate in risky behaviours. It was found that education level and GDP per capita are the critical factors affecting life expectancy in 28 European Union countries (Bilas et al., 2017). Similarly, Alcock and Kemp (1978) found that the education and wealth variables play a significant role in determining the life expectancy disparities among the countries. A study based on 136 countries from 2002 to 2010 found that life expectancy is negatively affected by unemployment and inflation and positively affected by gross capital formation and gross national income (Monsef & Mehrjardi, 2015).

The analysis of the relationship between SES and life expectancy is confined to developed nations where longitudinal mortality data are available. Studies from various developed worlds have analysed the patterns and determinants of life span by inculcating racial, gender, ethnic, income, educational and employment status, etc., into their framework (Assari, 2018; Case & Deaton, 2021; Chetty et al., 2016; Cutler & Lleras-Muney, 2006; Kinge et al., 2019). The longitudinal data on mortality in India is not available. However, recent studies relating socioeconomic differences to lifespan variation have gained attention in India (Asaria et al., 2019; Kumari & Mohanty, 2020; Saikia et al., 2019). Innovative techniques and well-grounded methodologies have been applied to study these variations, even in countries like India, where data on mortality fluxed with SES are scarce and often incomplete (Kumar et al., 2019). Although the methodologies, context, and techniques vary between these studies, the conclusion is similar: Lower SES is invariably associated with lower lifespan.

Scarcity and incompleteness of death data pose a severe obstacle to analysing life expectancy at the regional level in India. The Sample Registration System does not provide data on the SES of deceased individuals. The sample size of death records from major health surveys such as NFHS, NSSO, and IHDS is inadequate for analysing regional life expectancy. The Annual Health Survey

(AHS) —the data used in this study— of India is also not suitable for generating life expectancy at the regional level. However, the sample size of death records is quite reasonable for statistical analysis.

Odisha witnessed an 8 to 10 per cent economic growth rate in recent years. However, regional disparity remains an essential challenge in Odisha. The KBK regions are still lagging behind the rest of the districts of Odisha. Individual characteristics are essential for health research, but the geographical setting also explains the difference in health inequality to a great extent (Curtis & Rees Jones, 1998). Scholars have divided the influence of place and space into two parts, namely the contextual and composition effects. The compositional effect stems from the heterogeneous distribution of individuals whose personal characteristics impact their health. A strictly compositional interpretation of geographic variation could suggest that individuals with comparable profiles would experience comparable health outcomes irrespective of their geographical location. The context considers the area-level variables like the socio-economic characteristics, job market, access to different resources, social connection, etc., in a particular area (Jen et al., 2009; Leyland & Groenewegen, 2020).

In this article, we have tried to understand the following research questions: What is the average lifespan in Odisha at the district level? How does the average lifespan vary between different socio-economic groups? Is there any geographical variation in the average lifespan in Odisha? We have analysed the socio-economic differences in mean age at death of 65444 deceased individuals aged >=15 in Odisha from 2007 to 2011. In the first part, of the artilce we have analysed district wise variations in mean age at death and its associated covariates, and in the second part, individual-level variations in predicted mean age at death by characteristics and SES of 65444 deceased individuals. We have analysed not just the individuals' effects of age at death in Odisha but also how regions play a pivotal role in explaining the differences in average life span.

Data

The paper has two sets of data sets to analyse the stated objective. Our primary data is the death records of individuals from the AHS. The other data sets are the macro level district-wise estimated variables published in various government reports and portals (the complete list of variables, their definitions, and sources are given in Table 1). The AHS was undertaken by the Registrar General of India in conjunction with the Ministry of Health and Family Welfare, Government of India, to generate a comprehensive benchmark of fundamental and crucial health metrics at the district level across the 284 districts of Empowered Action Group States (EAG) in India, namely Bihar, Jharkhand, Uttar Pradesh, Uttarakhand, Madhya Pradesh, Chhattisgarh, Odisha, and Rajasthan. The sampling units comprised villages in rural areas and Census Enumeration Blocks (CEBs) in urban areas.

Table 1: Data Sources and Description

Variables	Description	Data Source
Mean	The mean age of death in the district obtained from Annual Health Survey data (2007-11)	Authors' estimate from the Annual Health Survey data: I (2010-11), II-(2011-12) and III-(2012-13) round.
Literacy	Percentage of literate people in a district	Census (2011)
BMI	District-wise Percentage of Males aged 15-59 below normal BMI	National Family Health Survey (2015-16)
LMPCE	District-wise Log of monthly per capita consumption expenditure.	Estimates provided by Directorate of Economics & Statistics; Government of Odisha based on NSS 68th Round (2011-12).
PHC/CHC	Total area of the district divided by total number of PHC/CHC/Sub-Center	www.data.gov.in for year 2011
Forest	Percentage of area out of total area covered by forest in a districts	www.data.gov.in for year 2013
SC/ST	Percentage of SC/ST population to total	Census (2011) population in a district

The survey design employed in the AHS involved uni-stage stratified simple random sampling without replacement, except for villages with populations equal to or exceeding 2000, according to the 2001 Census, where a two-stage stratified random sampling approach was utilised. Villages were stratified into two categories: Stratum I included villages with populations less than 2000, while Stratum II encompassed villages with populations of 2000 or more. Villages with populations less than 200 were excluded from the sampling frame, ensuring that the aggregate population of such villages did not exceed 2 per cent of the district's total population. In Stratum I, entire villages were selected as sample units, whereas in Stratum II, villages were divided into geographically contiguous and mutually exclusive units known as segments, each comprising a group of Enumeration Blocks (EBs) with populations not exceeding 2000. From these segments, one was randomly selected to represent the village at the second stage of sampling. The AHS was conducted over three rounds: the baseline survey (2010-11), first updation (2011-12), and second updation (2012-13). During the baseline survey, the Mortality Schedule documented details of deaths among usual residents of sampled households occurring from January 1, 2007, to December 31, 2009; the first updation covered deaths from January 1, 2010, to December 31, 2010; and the second updation recorded deaths from January 1, 2011, to January 31, 2011, capturing information such as sex, age at death, and socio-economic characteristics of the deceased's household.

Methodology

The levels of income and consumption are not captured in the AHS surveys. The AHS has collected data on household ownership of durable and non-durable assets and access to various household amenities. We have formulated one wealth index based on the household's ownership of durables and non-durables assets by using principal component analysis (PCA). Based on the PCA score, the individuals are divided into five quintiles from poorest to richest. This methodology is popularly used to denote the household's economic status where household income data are unavailable. The educational attainment of deceased individuals is not provided in the AHS survey, but that of the household head of those deceased individuals is recorded in the survey. We have grouped the individual educational attainment of the household head into four groups: the illiterate, literate but below class 10th as primary, 10th and up to class 12th as middle, and graduate, postgraduate, diploma, and any other professional training as higher.

We have used exploratory data analysis such as correlation matrix and scatterplots for macro-level district-wise analysis of age at death. The individual data is analysed using the OLS regression model to understand socio-economic differences in age at death. The AHS data is hierarchical at two levels: district and primary sampling units (PSUs). In a multivariate setting, there is slight (1 to 2 per cent) variation at the district level, and the unique identifications of PSUs are missing from the AHS data.

Moreover, we have categorised the district into three regions based on the NSSO division.

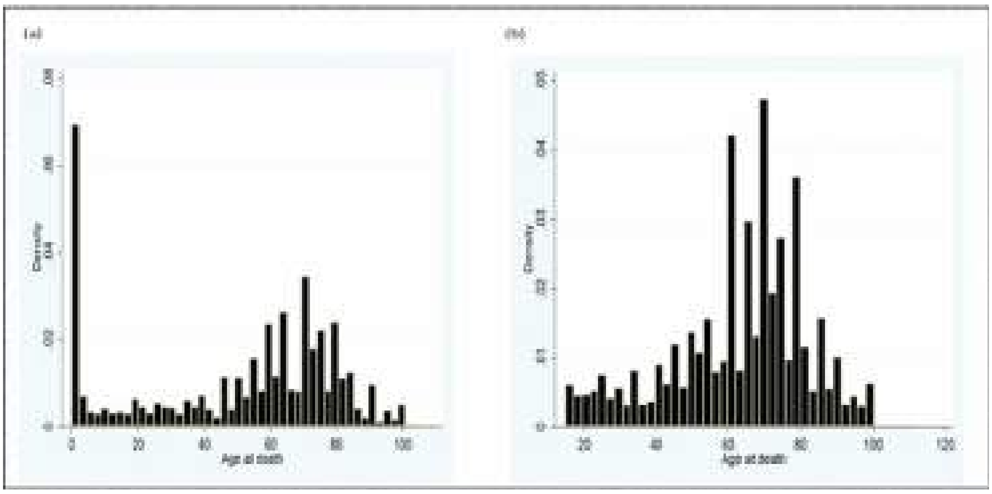
Results

Part-1

DistrictwiseDifferences in Mean Age at Death and Its Correlates

Panel-(a) of Figure 1 represents the age distribution at death for the total sample (N=94619). The distribution of death is hardly normal, as, in the case of Odisha, death is mainly concentrated among infants. This observation holdsfor all districts in Odisha (See supplementary Figures S1 and S2).

Figure 1: Distribution of Age at Death



Note: For the total sample in panel (a), N=94619, distribution of age at death from age 15 in panel (b), N=68444

In the 1950s, the global pattern of age at death exhibited primarily bimodal peaks, with a significant concentration among infants and a secondary peak in adulthood, varying in specifics across regions. With demographic and epidemiological transitions, societies experienced a notable shift towards a unimodal distribution centred on the mode of age at death. This shift reflects improvements in life expectancy and reductions in infant mortality rates. However, the improvement in age at death was uneven. Stagnation was observed in Asian and HIV-stricken countries of sub-Saharan

Africa in the 1990s (Permanyer & Scholl, 2019). Odisha is one of the states in India with high infant mortality rates. The age at death is mainly concentrated among infants in all the districts of Odisha, indicating high rates of infant mortality. In order to minimise the effect of this infant death on the mean age at death, the mean age at death from age >=15(N=65444) has been analysed both for macro and unit-levels. Figure 2 depicts the division of Odisha into three regions—northern, southern, and coastal based on data from the National Sample Survey (NSS).

Figure 2: The NSS Coastal, Northern and Southern Divisions of Odisha

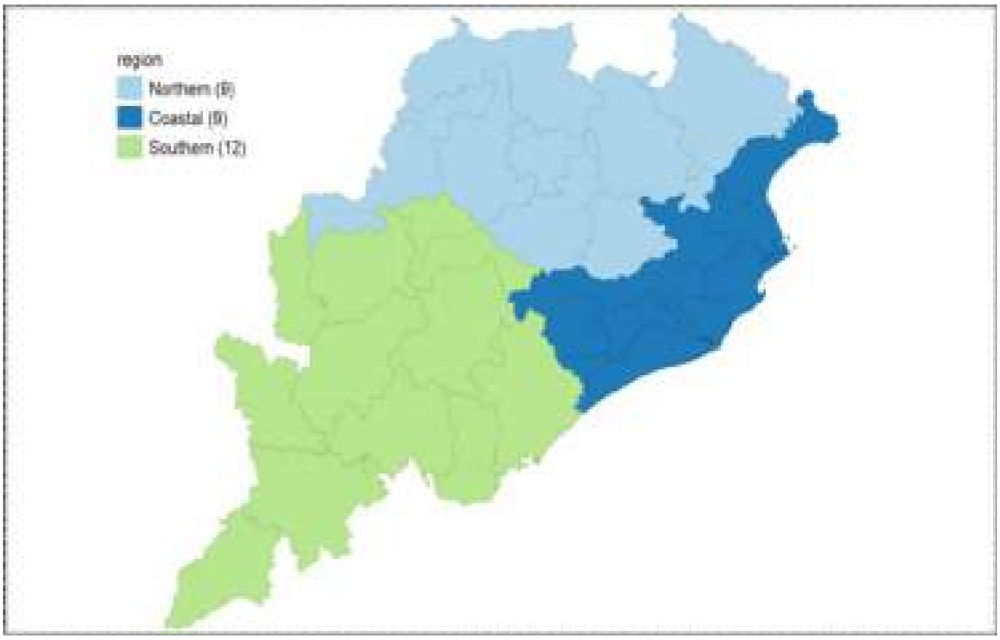
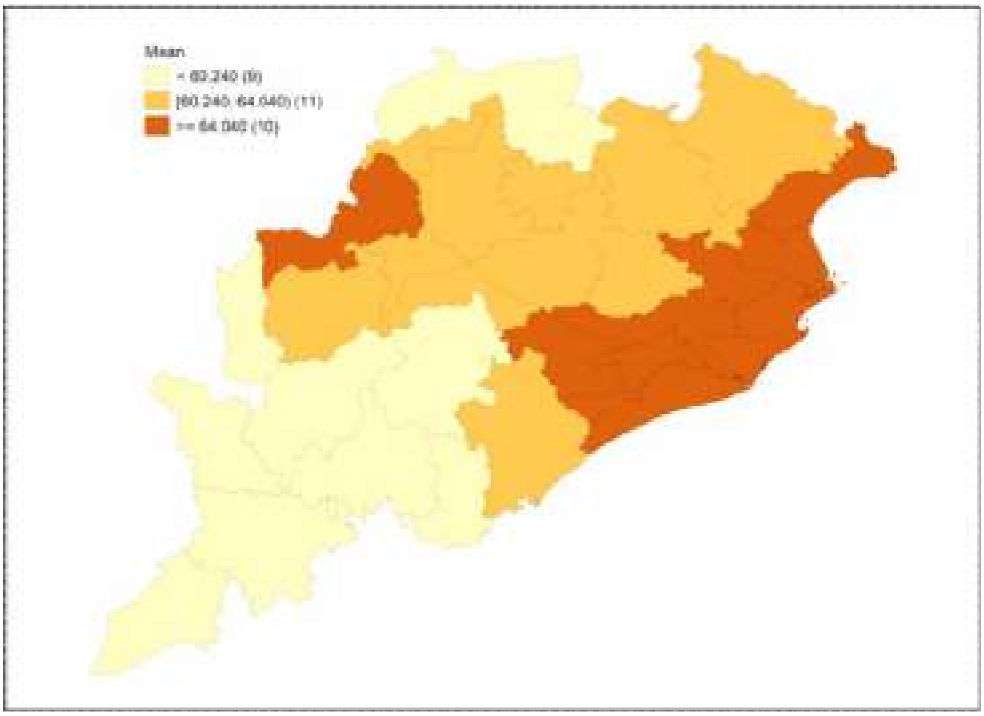


Figure 3 illustrates the mean age at death across these regions, revealing significant variation. Among these regions, coastal districts exhibit the highest mean age at death, while districts in southern Odisha have the lowest. Notably, Bargarh is the only district in the northern region where the mean age at death matches that of coastal districts.

Figure 3: District-wise Estimates of Mean Age at Death (weighted) in Odisha, India



Note: Estimated from AHS (2007-11), N=68444

The southern part of Odisha encompasses the economically disadvantaged KBK+ districts, characterised by lower development indicators. The highest average age of death was for Kendrapara district, and the lowest was for Malkangiri district. An attempt was made to understand these differences among the districts in the mean age of death by considering the district wise differences in literacy rate, body mass index, consumption expenditure, head count ratios, primary health centre/community health centre, forest coverage, SCs and STs.

Table 3 presents the summary statistics of district-level variables. The mean age at death ranges from a maximum of 67.6 years to a minimum of 53.6 years, indicating considerable variability across districts. Poverty incidence in the districts shows substantial disparity, ranging from 6 to 68 per cent, with a standard deviation of 20. Districts also exhibit varied levels of forest coverage, with an average of 28.5 per cent ranging from 2.5 per cent to 67 per cent of the total area covered. A significant proportion of Odisha's population belongs to SC and ST, ranging from 18.3 per cent to 84.4 per cent across districts, averaging 43.3 per cent.

Table 2: District-wise Descriptive Statistics

Districts	Mean	Median	Maximum	Std. Deviation	Coefficient of Dispersion	Coefficient of Variations (Mean)
Bargarh	64.269	68.000	100	18.470	0.204	28.7%
Jharsuguda	62.417	65.000	101	18.451	0.221	29.6%
Sambalpur	61.269	65.000	99	19.238	0.236	31.4%
Debagarh	61.679	65.000	99.	18.143	0.213	29.4%
Sundargarh	59.386	62.000	100	19.271	0.246	32.5%
Kendujhar	60.889	63.000	101	19.444	0.246	31.9%
Mayurbhanj	60.503	62.000	99	18.231	0.233	30.1%
Baleshwar	65.737	70.000	99	18.842	0.204	28.7%
Bhadrak	66.105	70.000	99	18.397	0.196	27.8%
Kendrapara	67.997	72.000	99	17.951	0.185	26.4%
Jagatsinghapur	66.273	70.000	99	17.633	0.196	26.6%
Cuttack	66.975	70.000	103	17.559	0.190	26.2%
Jajapur	65.783	70.000	99	18.476	0.200	28.1%
Dhenkanal	62.469	65.000	99	18.756	0.221	30.0%
Anugul	60.687	65.000	99	19.733	0.238	32.5%
Nayagarh	67.430	70.000	99	17.983	0.191	26.7%
Khordha	64.940	67.000	110	18.368	0.214	28.3%
Puri	66.400	70.000	105	18.115	0.195	27.3%
Ganjam	62.570	65.000	100	19.013	0.230	30.4%
Gajapati	58.557	61.000	103	18.256	0.237	31.2%
Kandhamal	59.638	63.000	99	19.279	0.240	32.3%
Baudh	62.430	65.000	99	19.749	0.235	31.6%
Subarnapur	62.948	65.000	110	18.650	0.220	29.6%
Balangir	61.625	65.000	99	19.028	0.225	30.9%
Nuapada	59.587	63.000	110	20.405	0.253	34.2%
Kalahandi	58.365	61.000	100	19.086	0.248	32.7%
Rayagada	57.221	60.000	102	18.713	0.245	32.7%
Nabarangapur	56.618	60.000	105	18.802	0.249	33.2%
Koraput	57.067	60.000	99	18.348	0.242	32.2%
Malkangiri	54.502	57.000	99	17.848	0.254	32.7%
Odisha	62.830	65.000	110	18.926	0.227	30.1%

Table 3: Descriptive Statistics Macro Level Variables

Variable	N	Mean	Std. Dev.	Min	Max
Mean	30	61.7	3.6	53.6	67.6
Literacy	30	70.8	12.5	46.4	86.9
BMI	30	20.8	5.3	9.8	30.4
LMPCE	30	3.1	0.1	3.0	3.2
HCR	30	39.2	20.0	6.0	68.0
PHC/CHC	30	21.6	10.7	7.1	55.5
Forest	30	28.5	16.8	2.5	67.0
SC/ST	30	43.3	18.5	18.3	80.4

Table 4: Correlation between the Mean age at death (Mean) and other predictors Variables

Variables	Mean	Literacy	BMI	HCR	LMPCE	PHC/CHC	Forest
Literacy	0.92***						
BMI	-0.51**	-0.53**					
HCR	-0.76***	-0.84***	0.39**				
LMPCE	0.70***	0.80***	-0.62***	-0.75***			
PHC/CHC	-0.53**	-0.40**	0.36**	0.62***	-0.43*		
Forest	-0.57**	-0.45**	0.20	0.57***	-0.22	0.69***	
SC/ST	-0.89***	-0.84***	0.44**	0.80**	-0.66***	0.49**	0.59***

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4 represents the correlation matrix of independent (mean age at death) and explanatory variables. It can be observed that not only is the mean age at death (Mean) highly correlated with the explanatory variables, but the explanatory variables are highly correlated with themselves. Districts with higher poverty (represented by Head Count Ratio), a higher percentage of males aged 15-59 having below normal BMI, a higher percentage of SC/ST, and higher forest coverage are negatively correlated with the mean. In contrast, higher literacy and monthly per-capita expenditure positively correlate with the mean.

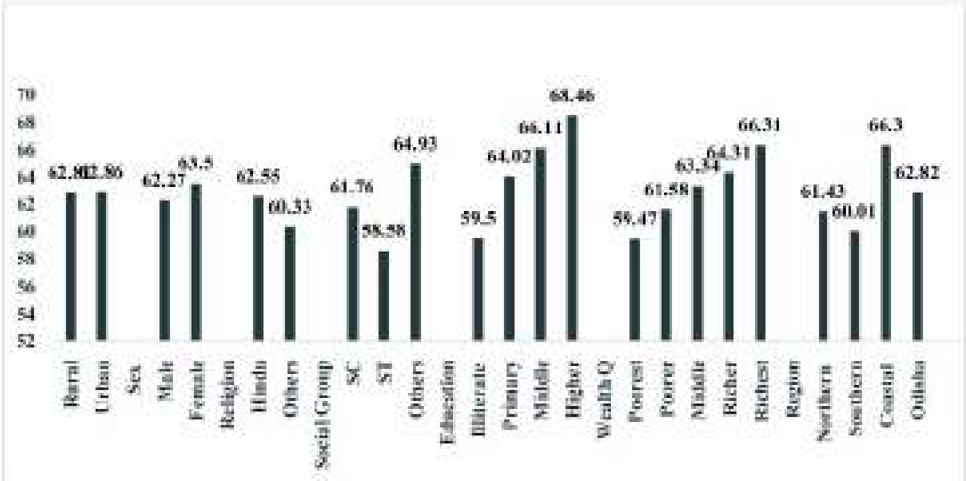
Part-2

Socio-economic Differences in Predicted Age at Death at the Individual Data

In the second phase, we examined the age at death of deceased individuals by integrating their socio-economic attributes. Descriptive statistics detailing these findings are provided in Supplementary Table A1. The socio-economic disparities in average age at death (weighted) are illustrated in Figure 4. A distinct stratification of average age at death is evident across SES rankings. Among the socio-economic categories, the most economically disadvantaged groups, namely the SCs and STs, exhibit a lower average age at death. Additionally, there exists a regional disparity in mean age at death, with the southern region displaying the lowest average. This observed disparity in mean age at death in the southern region may be attributed to higher levels of poverty, lower household consumption expenditure, limited access to healthcare services, and a higher proportion of the SC/ST population residing in that area.

The explanatory variables are significantly correlated with themselves, so it would be difficult to dissect the independent effect of each of these variables on mean in a multivariate regression framework due to the problem of multicollinearity. There are overlapping sets of deprivations in the districts of Odisha. Districts with high literacy will have lower poverty rates and monthly per-capita expenditures. Therefore, all the explanatory variables are plotted independently against the mean in Figure 5. The literacy, Head Count Ratio, and monthly per-capital expenditure are significantly associated with mean. The lower literacy rate, higher percentage of males below normal BMI, and lower monthly per-capita expenditure in the region could explain the lower mean in the southern region. The southern region also has a higher SC/ST population share, significantly predicting a lower mean (see Figure 5, panel-e). Access to healthcare is measured by the area covered by forest in a district (forest) and the district's total area in square kilometres divided by the total number of PHC/CHC/Sub-Center (PHC/CHC) in a district. Both of these proxy measures of access to healthcare show that access to healthcare increases the mean (see panels f and g) in Figure 5).

Figure 4: Socio-economic Differences in Mean Age at Death (Weighted) in Odisha



Note: N=68444

The summary statistics of deceased individuals and their background characteristics show that 85.84 per cent of deaths are in rural and 14.16 in urban (Table 5). It is interesting to note that rural Odisha has a better life span than urban Odisha. This variation in lifespan needs further exploration. Table 6 represents the predicted age at death from multivariate ordinary least square regression. Rural areas have a better lifespan than urban areas.

Figure 5: District-wise Association between Mean Age at Death and Major Relevant Variables

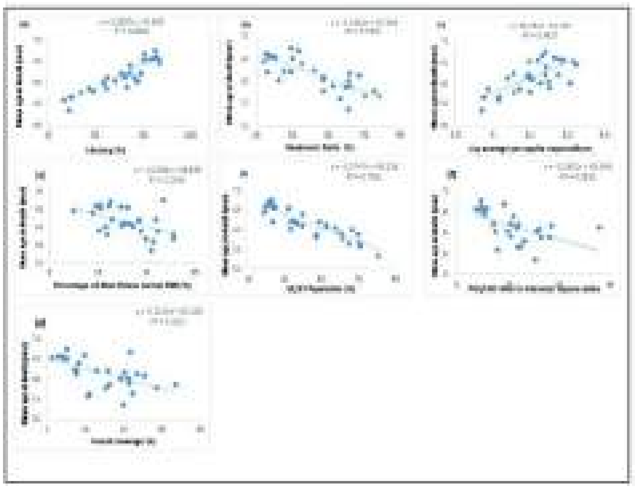


Table 7 depicts the predicted age at death obtained in the fully adjusted Model 2 of Table 6. The females have a higher mean age at death compared to the males. The Hindus have a better life span within the religious groups than others. Social group was found to be a significant predictor of mean age death. The difference in mean age at death between SC and others is 2.1, and between ST and Others is 3.06 years. Among the social groups, the ST is found to have a lower mean age at death. In model-1, only socioeconomic factors are adjusted in model-2; even after adjusting for education, wealth, and regional variation, the mean age at death improves for SC/ST, but the gap remains intact. Wealth, education, and regions are significant predictors in the multivariate OLS framework. The poorest and illiterate have a lower predicted death age than the richest and educated. The southern region has 5.01 years, and the northern region has 2.81 years lower mean age at death compared to the coastal region. The differences between the northern and southern regions were 1.8 years.

Table 5: Summary Statistics of Individual Level Variables (N=68444)

	Variables	N	Percentage	Mean	S.D	Maximum
Sector	Rural	58,753	85.84	66.93	18.02	108
	Urban	9,691	14.16	62.38	18.88	108
Deceased Sex	Male	37,704	55.09	62.65	19.21	110
	Female	30,740	44.91	63.77	18.46	110
Religion	Hindu	65,840	96.2	63.25	18.86	110
	Others	2,604	3.8	60.55	19.30	103
Social Group	SC	13,191	19.27	61.61	18.91	110
	ST	14,850	21.7	59.18	18.73	105
	Others	40,403	59.03	65.11	18.66	110
Wealth Q	Poorest	13,649	19.94	60.02	18.99	110
	Poorer	13,688	20	61.89	19.01	110
	Middle	13,696	20.01	63.49	18.74	110
	Richer	13,677	19.98	64.17	18.85	109
	Richest	13,734	20.07	66.16	18.25	108
Education	Illiterate	23,294	34.03	59.85	18.73	110

	Primary	33,545	49.01	64.09	18.89	109
	Higher Secondary	7,827	11.44	66.29	18.43	110
	Higher	3,778	5.52	68.61	17.25	101
Region	Northern	31,131	45.48	61.95	18.89	101
	Southern	12,390	18.1	59.93	19.15	110
	Coastal	24,923	36.41	66.24	18.29	110

Table 6: Results of Multivariate OLS Regression (Dependent Variable Age at Death: N=68444)

Variables	Background characteristics	Model-1			Model-2		
		Coefficients	$95\%CI^{L}$	$95\%CI^{U}$	Coefficients	$95\%CI^{L}$	$95\%CI^{U}$
Sector	Rural®						
	Urban	-1.45***	-1.86	-1.05	-2.85***	-3.28	-2.42
Deceased's Sex	Male®						
	Female	0.97***	0.69	1.25	0.75***	0.47	1.03
Religion	Hindu®						
	Others	-2.06***	-2.79	-1.33	-2.1***	-2.82	-1.37
Social	SC®						
Group	ST	-1.30***	-1.75	-0.85	-0.89***	-1.34	-0.44
	Others	3.34***	2.97	3.71	2.17***	1.8	2.55
Education	Illiterate®						
	Primary				2.47***	2.14	2.8
	Higher. Sc				4.09***	3.58	4.6
	Higher				5.91***	5.21	6.6
Wealth	Poorest®						
Quintile	Poorer				1.01***	0.56	1.45
	Middle				1.66***	1.21	2.12
	Richer				1.55***	1.08	2.01
	Richest				2.82***	2.3	3.34
Region	Northern®						
	Southern	-2.14***	-2.53	-1.75	-1.48***	-1.87	-1.09
	Coastal	3.07***	2.74	3.39	2.81***	2.48	3.14
	Constant	60.58***	60.19	60.97	58.03***	57.54	58.53

Notes:

(a) *** $p<0.01$, ** $p<0.05$, * $p<0.1$,

(b) Model-1: R-squared = 0.0235, Prob > F = 0.0000

(c) Model-2: R-squared= 0.0404, Prob > F = 0.0000

(d) ® Is the reference category

(e) CI^L,CI^U : Lower and Upper confidence interval

Table 7: Predicted Age at Death (Age*) from Multivariate Ordinary Least Square Model

Variables	Background	Model-1			Model-2		
	characteristics	Age*	95%CI^L	95%CI^U	Age*	95%CI^L	95%CI^U
Sector	Rural®	63.35***	63.20	63.50	63.55***	63.40	63.71
	Urban	61.90***	61.53	62.27	60.70***	60.31	61.09
Deceased's	Male®	62.71***	62.53	62.90	62.81***	62.63	63.00
Sex	Female	63.68***	63.47	63.89	63.56***	63.36	63.77
Religion	Hindu®	63.23***	63.08	63.37	63.23***	63.09	63.37
	Others	61.17***	60.45	61.89	61.13***	60.42	61.85
Social Group	SC®	61.46***	61.14	61.78	62.06***	61.74	62.38
	ST	60.16***	59.85	60.48	61.17***	60.85	61.49
	Others	64.80***	64.62	64.98	64.23***	64.05	64.42
Education	Illiterate®				61.14***	60.89	61.40
	Primary				63.62***	63.42	63.82
	Higher. Sc				65.23***	64.81	65.66
	Higher				67.05***	66.42	67.68
Wealth	Poorest®				61.74***	61.41	62.07
Quintile	Poorer				62.75***	62.43	63.07
	Middle				63.41***	63.09	63.72
	Richer				63.29***	62.97	63.60
	Richest				64.56***	64.20	64.91
Region	Northern®	62.42***	62.21	62.63	62.39***	62.18	62.60
	Southern	60.28***	59.95	60.61	60.91***	60.58	61.25
	Coastal	65.49***	65.25	65.73	65.20***	64.97	65.44

Notes:

(a) *** p<0.01, ** p<0.05, * p<0.1, Annual Health Survey data (2007-11), Odisha, India, N=65444

(b) ® is reference categories

(c) CI^L, CI^U-Lower and upper confidence intervals

Table 8: Interaction of Predicted Age at Death (Age*) of Social Group with Wealth and Education

Wealth	Age*	95%CI^L	95%CI^U
SC′ Poorest	60.65***	60.22	61.08
SC′Poorer	61.66***	61.24	62.07
SC′Middle	62.31***	61.90	62.73
SC′Richer	62.20***	61.77	62.63
SC′Richest	63.47***	62.99	63.95
ST′Poorest	59.76***	59.35	60.17
ST′Poorer	60.77***	60.35	61.18
ST′Middle	61.43***	60.99	61.86
ST′Richer	61.31***	60.87	61.75
ST′Richest	62.58***	62.09	63.07
Others′Poorest	62.82***	62.45	63.20
Others′Poorer	63.83***	63.48	64.19
Others′Middle	64.49***	64.15	64.83
Others′Richer	64.37***	64.04	64.70
Others′Richest	65.64***	65.29	66.00
Education			
SC′Illiterate	60.05***	59.68	60.43
SC′Primary	62.53***	62.17	62.88
SC′Higher Secondary	64.14***	63.62	64.67
SC′Higher	65.96***	65.26	66.66
ST′Illiterate	59.16***	58.80	59.53
ST′Primary	61.64***	61.27	62.00

ST′Higher Secondary	63.26***	62.73	63.78
ST′Higher	65.07***	64.37	65.77
Others′Illiterate	62.23***	61.93	62.53
Others′Primary	64.70***	64.47	64.93
Others′Higher Secondary	66.32***	65.88	66.76
Others′Higher	68.13***	67.50	68.77

Notes:

(a)*** p<0.01, ** p<0.05, * p<0.1,

(b) CI^L, CI^U-Lower and upper confidence intervals

Table 9: Interaction of Predicted Age at Death (Age*) of a Social Group, Education and Wealth with the Region, Obtained from Fully Adjusted Model-2, Table 3

Social groups and region	Age*	95%CI^L	95%CI^U
SC′ Northern	61.30***	60.94	61.67
SC ′Southern	59.82***	59.39	60.26
SC′ Coastal	64.11***	63.75	64.48
ST ′Northern	60.41***	60.09	60.74
ST ′Southern	58.94***	58.50	59.37
ST ′Coastal	63.23***	62.81	63.64
Other′ Northern	63.48***	63.22	63.74
Others′ Southern	62.00***	61.64	62.36
Others ′Coastal	66.29***	66.04	66.54
Education and Region			
Illiterate ′Northern	60.39***	60.08	60.69
Illiterate′ Southern	58.91***	58.54	59.28
Illiterate ′Coastal	63.20***	62.87	63.53
Primary ′Northern	62.86***	62.61	63.11
Primary′ Southern	61.38***	61.01	61.76
Primary ′Coastal	65.67***	65.40	65.95
Higher Sec ′Northern	64.48***	64.02	64.93

Higher Sec′ Southern	63.00***	62.47	63.53
Higher Sec. ′ Coastal	67.29***	66.82	67.75
Higher ′Northern	66.29***	65.64	66.94
Higher ′Southern	64.81***	64.11	65.52
Higher ′Coastal	69.10***	68.46	69.75
Wealth and Region			
Poorest ′Northern	60.98***	60.62	61.35
Poorest ′Southern	59.51***	59.07	59.94
Poorest Coastal	63.80***	63.40	64.19
Poor ′Northern	61.99***	61.64	62.34
Poor ′Southern	60.51***	60.08	60.95
Poor ′Coastal	64.80***	64.42	65.18
Middle ′Northern	62.65***	62.30	63.00
Middle ′Southern	61.17***	60.73	61.61
Middle′ Coastal	65.46***	65.10	65.82
Richer′ Northern	62.53***	62.18	62.89
Richer′ Southern	61.05***	60.61	61.50
Richer ′Coastal	65.34***	64.98	65.71
Richest ′Northern	63.80***	63.42	64.19
Richest′ Southern	62.32***	61.85	62.79
Richest′ Coastal	66.61***	66.21	67.02

Notes:

(a)*** $p<0.01$, ** $p<0.05$, * $p<0.1$,

(b) CI^L, CI^U-Lower and upper confidence intervals

Table 8 represents the interaction of SC/ST with education and wealth for the predicted age at death obtained from the fully adjusted multivariate OLS Model-2. The results indicate that with the same education level and wealth quintile, there is a significant difference in predicted age at death between the social groups. The SC and ST with higher education have 2.17 and 3.06 lower predicted age at death than other social groups with higher education. Similarly, the SC and ST of the richest wealth quintile have 2.17 and 3.06 lower predicted age at death than the other social groups of the wealthiest quintiles. The gap in the predicted age existed between the social groups with similar wealth and education levels. The interaction effects of social class, wealth, and education with the region are given in Table 9. The region substantially contributes to the gap in the predicted age at death. The individuals with similar socio-economic characteristics residing in the different areas of Odisha were found to have different ages at death.

Discussion

Lifespan or life expectancy is one of the benchmark measures of development. Disaggregated and regional-level life expectancy estimates are impossible to calculate for developing countries, including India. With the recent advent of Demographic and Health Survey data, there is considerable research on life expectancy at the disaggregated level in India. In this article, we have used two data sets to analyse age at death in Odisha. In the first data set, we estimated the district-wise mean age at death from age 15 of 65444 deceased individuals. The district-wise mean age at death and its relationship with district-wise development indicators obtained from various government reports and publications are analysed. In the second part of our analysis, we estimated the predicted age at death for 65444 individuals from 2007-11, considering their socio-economic position in a multivariate ordinary least square regression framework.

The findings reveal significant variability in mean age at death across districts, with districts in the southern region of Odisha exhibiting the lowest average age at death compared to those in the coastal and northern regions. This pattern is further supported by the predictions from the OLS model, which consistently indicate lower predicted ages at death in the southern region. Exploratory data analysis, including interactive scatter plots, underscores that the lower mean age at death observed in southern Odisha can be attributed to factors such as high levels of poverty, lower literacy rates, reduced household consumption expenditures, limited access to healthcare services, and a higher proportion of SC and ST populations in the region.

The disparity in various development indicators, such as income, poverty, education, and healthcare, is a prominent characteristic of Odisha. Scholars have extensively studied this regional inequality, which persists despite ongoing efforts (de Haan & Dubey, 2005; Jha, 2017). The southern districts notably lag behind their coastal counterparts across multiple development metrics in Odisha.

The southern region of Odisha comprises the backward KBK+ districts, which are considered the state's most backward districts. Studies have noted that Odisha has substantially reduced poverty; however, the poverty rate in the southern and northern regions is lagging behind the rest of the state (Panda & Padhi, 2020). As we have shown through our exploratory data analysis, lower levels of literacy, lower consumption expenditure, and a high percentage of the SC/ST population could be the reason for the lower average lifespan in the southern districts of Odisha.

The education of the household head and the wealth quintile of the deceased individual are significant predictors of predicted age at death. The evidence from previous studies in India and studies from different countries suggests that lower SES is negatively linked to life expectancy. The possible mechanism through which education, wealth, and other SES can influence health outcomes is that good SES may result in better access to resources and healthcare (Cutler et al., 2008; Cutler & Lleras-Muney, 2006).

Individuals with high educational attainment have better living conditions and lifestyles, maintain good health, and invest in healthcare than those with poor educational attainment. Educational attainment puts an individual earning jobs with health insurance in an innocuous working environment. Education leads to cognitive development, critical thinking, and access to better information. Educated persons can decide on new health information and use it. Education leads to more socialisation that creates physical, emotional, and financial support for him/her during hard times and better health. Investment in healthcare requires economic and financial improvement and proper health to enhance the working capacity of individuals with better performance in the job sector and higher earnings (Cutler et al., 2008; Cutler & Lleras-Muney, 2006).

The predicted age at death from the multivariate regression model indicates that the SC and ST are the social groups with the lowest predicted age, even after controlling for wealth, education, and other demographic factors. The persistence of caste in India plays a decisive role in access to many resources and social networks, and caste in India is one of the proxy measures of SES. Various studies highlight significant caste-based differentials in vital health indicators and healthcare utilisation among the different caste groups. In India, adult mortality and life expectancy for SC and ST are much lower than other social groups (Kumari & Mohanty, 2020; Mohanty & Ram, 2010; Saikia et al., 2019). The interaction of predicted age at death of different social groups with wealth and education signifies that SC/ST with similar educational attainment and wealth to the other social groups have lower predicted age at death. According to Link and Phelan (1995), SES is a fundamental cause of health disparity. The higher SES people possess various resources, power, money, and beneficial social connections that protect themselves at any given time in different diseases environments.

Phelan and Link (2015) have expanded their theoretical framework to encompass racial disparities in health. They posit that race constitutes a fundamental determinant of differential SES and access to flexible resources such as power, prestige, advantageous social connections, and freedom, irrespective of SES. Moreover, race correlates independently with various health outcomes. In India, caste is associated with SES and the possession of flexible resources like power, prestige, freedom, and beneficial social connections (Bharti, 2018; Mosse, 2018; Munshi, 2019; Newman & Thorat, 2010; Phelan & Link, 2015). Evidence suggests that SCs and STs experience lower life expectancy compared to other social groups with similar educational attainment and wealth quintile, indicating that caste may function as a fundamental determinant of lifespan disparities. Furthermore, disparities across different geographical contexts warrant heightened attention. An optimistic outlook towards addressing disparities in longevity rooted in social and regional identities may well be linked to protective measures adopted by the government regarding access to healthcare like that of the Ayushman Bharat Digital Mission. This may be considered a policy initiative designed to advance healthcare in India. It holds considerable promise for reducing overall health disparities through various mechanisms, including providing health insurance to economically disadvantaged populations, improved access to high-quality medical care, the development of healthcare infrastructure, and reducing health disparities by promoting equitable access to healthcare services.

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This paper is based on simple statistics, such as estimated district-wise mean age at death, and simple exploratory statistics rather than more advanced methods, such as life expectancy, based on methods such as life tables. We must rely on such statistics because mortality data from India’s foremost national survey is unavailable. Though the AHS has a reasonable sample size, the data is incomplete. One limitation is the unavailability of access to healthcare data in the AHS mortality schedule. While this study did not distinguish between the separate effects of contextual and compositional factors, interaction effects suggest pronounced geographic disparities in age at death.

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Supplementary Figures and Tables

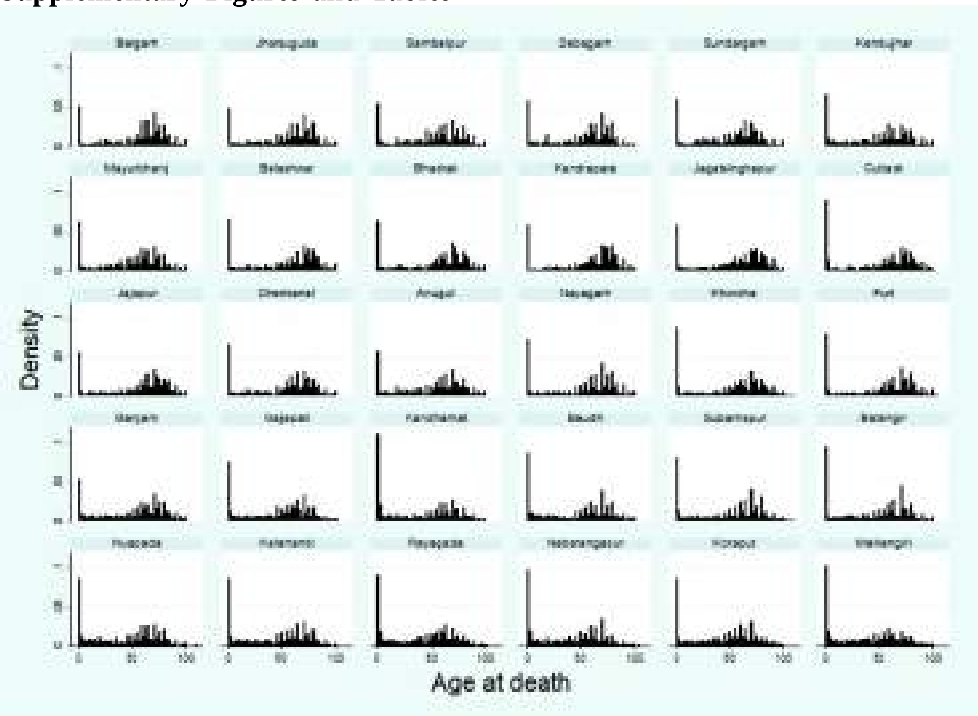

Figure S1: District-wise distribution of age at death (2007-11) full sample, N=92999, Odisha, India

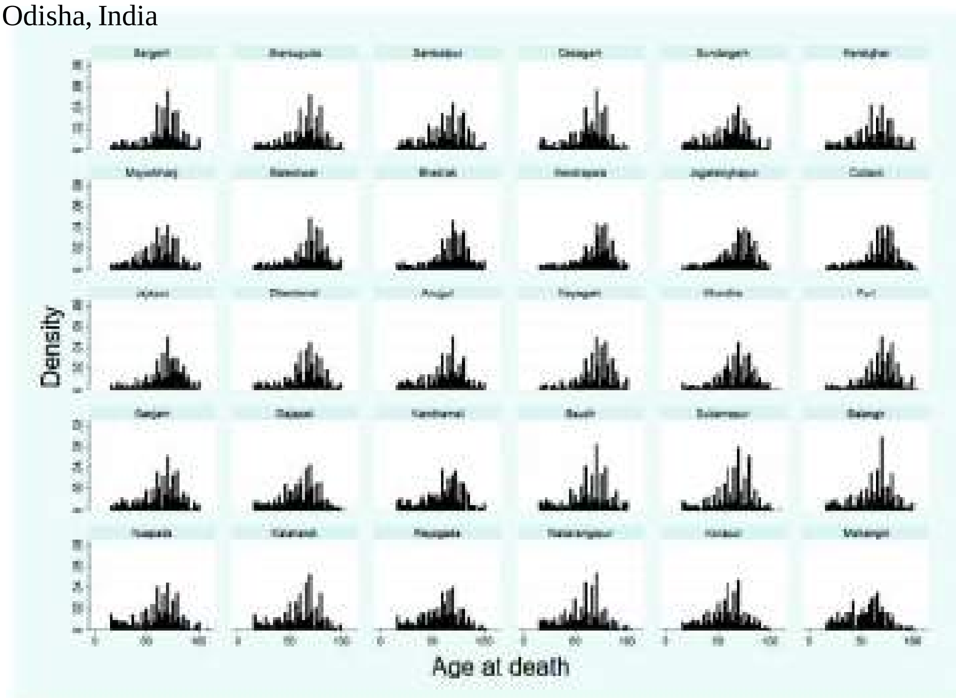

Figure S2: District-wise distribution of age at death form from age 15 (2007-11), N=65444, Odisha, India

Supplementary Table A1: Summary Statistics

Variables	N	Percentage	Mean	S. D	Maximum
Sector					
Rural	58,753	85.84	66.93	18.02	108
Urban	9,691	14.16	62.38	18.88	108
Deceased Sex					
Male	37,704	55.09	62.65	19.21	110
Female	30,740	44.91	63.77	18.46	110
Religion					
Hindu	65,840	96.2	63.25	18.86	110
Others	2,604	3.8	60.55	19.30	103
Social Group					
SC	13,191	19.27	61.61	18.91	110
ST	14,850	21.7	59.18	18.73	105
Others	40,403	59.03	65.11	18.66	110
Wealth Q					
Poorest	13,649	19.94	60.02	18.99	110
Poorer	13,688	20	61.89	19.01	110
Middle	13,696	20.01	63.49	18.74	110
Richer	13,677	19.98	64.17	18.85	109
Richest	13,734	20.07	66.16	18.25	108
Education					
Illiterate	23,294	34.03	59.85	18.73	110
Primary	33,545	49.01	64.09	18.89	109
Higher Secondary	7,827	11.44	66.29	18.43	110
Higher	3,778	5.52	68.61	17.25	101
Region					
Northern	31,131	45.48	61.95	18.89	101
Southern	12,390	18.1	59.93	19.15	110
Coastal	24,923	36.41	66.24	18.29	110

Supplementary Table A2: List of Variables Used for the Construction of the Individual's Wealth Index

Type of structure of the House Main sources of drinking water	Pucca House=1, Otherwise =0 Pipe water into dwelling/ yard/ plot, public tap/ stand pipe, hand pump, tube well or bore well, protected dug well =1 otherwise = 0
Type of toilet facility mainly used	Flush/ pour latrine-connected: to pipe sewer line/ septic tank/ pit latrine/ somewhere else, pit latrine (without flush/pour flush): ventilated improved pit, pit latrine with slab=1, otherwise =0
Household having electricity	Yes=1 No=0
Main source of lighting	Electricity, Solar=1, Otherwise =0
Main source of fuel used for cooking	LPG/PNG, Electricity, Biogas=1, Otherwise=0
Number of dwelling rooms exclusively in the possession of household	Household having no dwelling room exclusively in possession=0, 1 dwelling room exclusively in possession=1, 2 dwelling room exclusively in possession=2, 3 dwelling room exclusively in possession=3, 4 dwelling room exclusively in possession=4, 5 dwelling room exclusively in possession=5, 6 dwelling room exclusively in possession=6, 7 dwelling room exclusively in possession=7, 8 dwelling room exclusively in possession=8, 9 or more dwelling room exclusively in possession =9
Availability of kitchen	Cooking inside or outside House- Has kitchen=1, Otherwise =0
Possession of Radio/transmission	Yes=1 No=0
Possession of Television	Yes=1 No=0
Possession of computer/ laptop	Computer or laptop with or without internet connection =1 No= 0
Possession of Telephone/ mobile phone	Telephone or Mobile phone or Both=1, No=0
Possession of Washing machine	Yes=1 No=0
Possession of Refrigerator	Yes=1 No=0
Possession of sewing machine	Yes=1 No=0
Possession of Bicycle	Yes=1 No=0

Possession of Two-wheeler (scooter, motorcycle, moped)	Yes=1 No=0
Possession of car/jeep/ van	Yes=1 No=0
Possession of tractor	Yes=1 No=0
Possession of water pump/ tube well Possession of cart (driven by animal/ machine/ others)	Yes=1 No=0 cart driven by animal/ machine/ others=1, does not have =0
Land possessed (in hectare)	No land=0, less than 0.02 hectare=1, 0.02 to less than 1 hectare=49, 1 to less than 4 hectares =250, 4 to less than 10 hectares =700, 10 hectare or more= 1000

Article

Competitiveness in Cereals: Navigating Non-Tariff Measures and Environmental Decline in a New Trade Framework

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Abstract

Since the World Trade Organisation's formation, the period (1996-2020) has witnessed changes that altered the nature and conduct of trade. The long-run analysis seeks to uncover the factors affecting cereals' competitiveness in this new trade framework. To understand the interrelated factors, an exploratory factor analysis is used to group similar variables. It is followed by a fully modified ordinary least squares method for long-run estimation. The analysis is conducted both for India and BRICS as a whole. The findings reveal the importance of agriculture value added in GDP (resource allocation factor) and the trade-hindering nature of non-tariff measures. A case has been made for efforts at value addition to tap into the full potential for competitiveness in cereals.

Keywords: International trade, Comparative advantage, environment, Agricultural commodities, BRICS

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Introduction

The key determinants influencing the agricultural trade of cereals (HS-10) within a new trade framework between 1996 and 2020 form the key elements of this analysis. The study explores the new trade framework which became prominent since the formation of World Trade Organisation (WTO). The new trade framework includes the rise in global value chains, resource constraints and increase in regulatory requirements especially from the advanced nations. Cereals are a prominent commodity in the BRICS (Brazil, Russia, India, China and South Africa) countries which have vast trading networks comparable to G7 and the European Union regarding exports and geographical area. A significant amount of trade happens within BRICS as well. China is a major trading partner for most of the BRICS nations. Intra-BRICS exports experienced a 9.3 per cent growth even though it remained at six per cent from 2014 to 2018 (Duric & Glauben, 2024). BRICS countries always have a comparative advantage in products like soybeans in Brazil and cereals in India. However, self-sufficiency at home often fails to reciprocate a similar level of competitiveness for agricultural products internationally. The paper analyses this self-sufficiency-competitiveness gap within the new trade framework. The analysis involves using environment-related variables, such as arable land, temperature change, and other crucial determinants of trade, such as real effective exchange rates, terms of trade, production, and prices.

India has proved to be a powerhouse of agriculture production despite lacking food accessibility and availability. In the Agriculture Export Policy 2018, India set a target of 100 billion dollars in exports by 2026 (Roy et al., 2022). On the competitiveness of exports, India has achieved a level of competency through its resources, large-scale production, and trade. However, here, the level of competitiveness is different from the self-sufficiency India currently enjoys in commodities like cereals. Cereal production has increased more than 1.5 times in the last two decades. The average annual growth is 2.5 per cent during the last ten years. Major cereal crops include rice, wheat, and maize (Damodaran, 2024). Even though India produces 300 million tonnes of cereals (primarily rice and wheat) annually, India's competitiveness in the global market is limited. There is a widening gap between the production and consumption of cereals, with multiple challenges in maintaining competitiveness.

There is also a lack of diversification in cereals, especially at the disaggregate level. The only product which shows up as highly competitive for cereals (HS-6 category) out of all commodities is Cereals; rice, semi-milled or wholly milled, whether or not polished or glazed (HS-100630). The rest of the products have much lower ranks. Similarly, India lost a competitive edge due to the higher standards required by the leading importers. The need for international standards denied its entry into the premium markets. In addition to the above woes, India often fails to keep the export commitments despite the data which shows adequate domestic supply. India's competitiveness in exporting cereals is influenced by global market conditions and the quality of its produce. Narayan and Bhattacharya (2019) pointed out that wheat suffered comparative disadvantages post-2006, while rice had the best comparative advantage compared to products like sugar, cotton, and wheat.

In the case of BRICS, Brazil is a major producer and exporter of cereals, particularly maize and wheat. Russia is a significant producer and exporter of wheat. China is a large producer of cereals, with a focus on ensuring food security and self-sufficiency in staple crops like rice and wheat. South Africa is a net exporter of cereal crops, with maize being the primary commodity. South Africa has tried expanding its cereal export market (Drèze & Oldiges, 2024).

Review of Literature

Climate Change and Agricultural Competitiveness: Literature covering the concept of environmental impacts on trade is relatively recent. Bozzola et al. (2023) explain that climate change will bring comparative advantages across nations. The environmental changes will result in more instances of the shift from comparative advantage to comparative disadvantage and vice versa (Goswami & Nath, 2021). According to Nugroho et al. (2023), agricultural competitiveness raises temperature in developing countries while decreasing temperatures in developed countries. In reducing competitiveness, temperature change has the same effect in both nations. Several studies discussed land as a factor, especially the production and consumption-based use of arable land (Chen & Han, 2015: Jambor et al., 2016: Narayan & Bhattacharya, 2019: Wu et al., 2018). The studies have also pointed out that climate is an exogenous factor typically affecting productivity (Mendelsohn et al., 1994: Knittel et al., 2020) and can alter comparative advantage. Competitiveness here refers to a country's ability to produce a product at a lower cost than others. Consequently, it leads to export (import) and excess supply (demand) (Latruffe, 2010). Similarly, a study by Joshy and Kareem (2024) shows a positive relationship between arable land use and terms of trade stability in BRICS

Non-Tariff Measures (NTMS) and Other Trade Determinants: The non-tariff measures became a roadblock for developing and developed nations (to some extent) since the Doha round negotiations. Many studies, such as Kaur and Sarin (2017), Fathipour and Gaikwad (2018) and Maryam and Mittal (2019), pointed out the critical nature of non-tariff barriers in affecting agriculture trade. According to Montalbano and Nenci (2020), tariffs and non-tariffs present a substantial obstacle to GVC participation. Disdier et al. (2008) pointed out that including non-tariff measures, such as Sanitary and Phytosanitary (SPS) measures and technical barriers to trade (TBTs) measures, significantly negatively affects imports across all models. Maertens and Swinnen (2015) argued that the proliferation of public and private standards has created more non-tariff barriers in agriculture trade. Therefore, the study aims to address an essential gap in the literature through the inclusion of non-tariff measures.

Mizik (2021) identifies the major factors that contribute to higher agri-food trade competitiveness, such as supportive legislation and trade policy, higher value-added/ more sophisticated goods, and high, efficient, and profitable production. Similarly, Paul and Dhiman (2021) pointed out that labour and capital productivity, labour costs, exchange rate, real effective exchange rate (REER), gross domestic product (GDP), trade liberalisation, and trade barriers are major influencing determinants of trade competitiveness. The study on the export competitiveness of key cereals from India showed that maize performed well in production, while most cereals, except rice, lost export competitiveness later (Kumari & Suseela, 2023).

Trade Theories and Competitiveness Indices: Białowąs and Budzyńska (2022) suggested using trade specialisation indexes like Lafay to capture the competitiveness within the fragmented trade that is seen today. Trade fragmentation offers a challenge to trade indices such as RSCA (Revealed Symmetric Comparative Advantage) in accounting for reexport flows. In this context, Lafay is considered the best measure of specialisation and comparative advantage by numerous studies, including Zaghini (2003), Ferrarini and Scaramozzino (2011), and Goswami and Nath (2021). Lafay is more relevant in value chain-based trade as it accounts for reexport flows. A review study by Paul and Dhiman (2021) pointed out that most studies on export competitiveness focused on the Hecksher-Ohlin theory, the theory of comparative advantage, and the product life cycle theory.

The literature has failed to assess the systemic nature of trade competitiveness. For instance, Latruffe (2010) pointed out that competitiveness incorporates various aspects and is a broad and evolving concept. Similarly, a dynamic approach to competitive performance is relevant because it incorporates business, structural, and systemic determinants. In other words, competitiveness is essentially systemic (Medeiros et al., 2019). Trade patterns depend on diverse factors related to the products under consideration. One factor is that movement can impinge upon the movement of a few others. The various factors are related to the main mechanisms of trade stressed by different trade theories (Onderzoekverslag and Meijl, 1998). Therefore, through this paper, the study fills an essential methodological gap with the help of an exploratory factor analysis, followed by a long-run estimation. The study also seeks to explore these determinants for India and BRICS, and within BRICS and the world.

The unique aspect of this study is that it focuses on the impact of a combination of essential determinants of agriculture trade competitiveness for products at the aggregate level. So far, the literature has addressed only individual determinants in studying competitiveness. In a new trade framework, where multiple effects occur, the variables influence each other as demand and supply side variables. To undertake this on a panel data model, exploratory factor analysis is used to identify the variables that belong to the same factor, followed by the FMOLS (Fully Modified Ordinary Least Squares) method to assess the long-run relationships. Also, as a dependent variable, the Lafay trade balance index emphasises exports and imports, thus shedding light on the imbalance of the factors under consideration within the new trade framework. The study raises the following research questions: Does the new trade framework explain the product-level agriculture trade competitiveness of BRICS nations? If yes, what factors constitute the new trade framework that can influence trade competitiveness?

Objectives

The study analyses the emerging determinants of cereal trade competitiveness in India and in BRICS within the new trade framework.

Methodology and Data

Exploratory factor analysis reduces the number of variables and groups related ones into common factors (the variables with an eigenvalue above one). The EFA method has identified six factors. The variables loaded strongly (above 0.4) belong to a particular factor. The rotation method used was varimax and extraction was done using principal component analysis.

The present study covers the impact of determinants (environmental and non-environmental) on the competitiveness of agriculture products within BRICS and the world.

The ARDL FMOLS (Autoregressive Distributed Lag Fully Modified Ordinary Least Squares) Model can be specified as follows:

$$L_{it} = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \ldots + \beta_k X_{kt} + \epsilon_t$$

$$LFI = 100\left(\frac{x_j - m_j}{x_j + m_j} - \frac{\sum_{(j=1)}^{N}(x_j - m_j)}{\sum_{(j=1)}^{N}(x_j + m_j)}\right) * \frac{(x_j + m_j)}{\sum_{(j=1)}^{N}(x_j + m_j)}$$

Where

Y_t represents the dependent variable (e.g., trade competitiveness),

$X_{1,t}, X_{2,t}, \ldots, X_{k,t}$ are the independent variables (factors),

α is the intercept term,

$\beta_1, \beta_2, \ldots, \beta_k$ are the coefficients representing the long-run impact of the independent variables on the dependent variable and

$\tilde{o}_t$ is the error term, corrected for serial correlation and endogeneity.

The dependent variables for six of the seven chosen products are Lafay index values within the BRICS trade bloc (as Lafay facilitates this calculation) and the world. The independent variables are arable land use, Agriculture Value Added in GDP (AVA_GDP), commodity terms of trade, Grubel-Lloyd index 8 and 3 (i.e., fruits, nuts and edible products and fish and crustaceans), simple average tariffs, trade openness, product differentiation, GVC participation index, GL_index 6,9,10,7,12,17, producer prices, agriculture trade costs (bilateral), temperature change, world demand, real effective exchange rate, agriculture production, income per capita, AVA_worker, purchasing power parity in GDP. Exploratory factor analysis groups the chosen 24 variables into six different factor groups.

The study uses the UN COMTRADE database. The data on the SPS measures and TBTs regulations from the Indian Institute of Foreign Trade (IIFT) database provides a new dimension. Other significant data sources include the World Bank database, Our World in Data, the OECD database, the IMF database, the WITS database, the MOSPI database, the EORA database for global value-added trade data, and the UNCTAD database.

Table 1: Im–Pesaran–Shin (IPS) Unit Root Test

Variable	Level Statistic	Level p-value	First Difference Statistic	First Difference p-value
LaFayCf	-2.7952	0.0026		
LaFaycereals	-0.1891	0.4250	-6.8771	0.0000

The Im-Pesaran-Shin unit root test is a panel data test used to determine whether a time series is non-stationary (contains unit root) across multiple cross-sections. The null hypothesis (H0) is that all panels contain unit roots (i.e., the series is non-stationary in all cross-sections). The alternative hypothesis (Ha) is that some panels are stationary. In Table 1, the p-value for 'lafaycf' (within BRICS) is stationary at the level. This implies no unit root, and the series requires no differencing. However, for cereals, the Lafay value (at the world level) shows non-significance at a level (0.4250). This indicates that it is not possible to reject the null hypothesis. However, after differencing once, the p-value becomes 0.0000, and the statistic is -6.8771, which is highly significant. This suggests that the 'LaFaycereals' series is stationary after first differencing, indicating it is integrated of order 1 (I (1)). The Lafay trade specialisation index likely follows long-term trends due to structural changes in trade patterns, comparative advantage shifts, etc. Similarly, factors extracted through EFA also show a non-stationary nature due to the influence of underlying variables.

Conceptual Framework

The factors identified through exploratory factor analysis, such as regulatory compliance and economic accessibility, resources and policy-driven trade, inflationary pressures, macroeconomic stability and production-driven trade, trade stability and value chain integration, and product diversity and economic capacity, align well with the New Trade Theory (NTT), which is an improvement over the Hecksher-Ohlin models. It discusses the role of increasing returns that occur as a result of specialisation.

In addition to NTT, a specific factor model establishes a vital link. The model states that when exports rise, the owners of fixed capital, like land, benefit. The key lesson here is that changes in trade patterns fall mainly upon fixed factors such as land.

The economic rationale behind each factor is as follows: -

1. Regulatory compliance and economic accessibility – According to the NTT, higher incomes drive trade openness and specialisation. Raising farmers' incomes provides an opportunity to integrate local products into value chains. However, SPS/ TBT measures can act as trade barriers (Ullah et al., 2024).

2. Resource allocation and policy-driven trade – Higher AVA_GDP (an indirect proxy for technological change) can indicate more competent use of arable land in producing goods for export. It is essential for understanding agricultural trade's financial impact (Chen & Han, 2015). Trade liberalisation enhances the process of technology transfer as trade barriers are lifted (Wang, 2023). Terms of trade externality means how one country's policies can impact the trade of others. It is one of the rationales to arrive at trade agreements.

3. Inflationary pressure and resource dynamics - Specific factor models link trade changes to fixed factors like land. As per the recent literature temperature changes affect production costs and agricultural value-added per worker (Nugroho et al., 2023). BRICS economies experience price transmissions and volatility spillovers due to interlinkages especially in agri-food markets. It influences intra-industry trade (Frey & Manera, 2007).

4. Macroeconomic stability and production-driven trade – A favourable real effective exchange rate (REER) boosts agricultural export competitiveness. FDI contributes to better yield through technology and infrastructure. Likewise, it is mentioned in the literature that a stable REER attracts FDI into agriculture (Mizik, 2021).

5. Trade stability and value chain – Global value chains (GVCs) have surpassed intra-industry trade in shaping production networks (Jones, 2018). Specialisation within global value chains enables intermediate trade in agriculture. It reduces trade instability (Montalbano & Nenci, 2020).

6. Product diversity and economic capacity – New Trade Theory explains similar product trade through economies of scale. Purchasing power parity (PPP) influences trade costs and intra-industry trade. It shapes consumer preferences and production structures.

The new trade framework in the study expands the theoretical base provided by modern trade theories. The new trade framework encompasses variables that became more relevant during the study period (1996-2020). The period marks the formation of the WTO. It led to the rise of global value chain-based trade. Similarly, the period is also known for increased regulatory requirements through non-tariff measures due to sustainability concerns. The year 1995 marked the beginning of India's integration into WTO. India also embarked on trade liberalisation policies during the early 1990s. Other BRICS nations also followed a similar path.

The period also saw a rise in global average temperatures and a serious concern for land degradation. Climate change and resource depletion alter comparative advantages, and these factors can shift nations' trade dynamics from comparative advantage (CA) to comparative disadvantage (CDA). So, in the context of the above changes witnessed in global trade, the study frames the hypothesis that the new trade framework influences the product-level trade competitiveness of cereals.

Results and Discussion

The highest loading factor is taken for each variable and considered under that group. These factors are as follows: Factor 1 –Regulatory compliance and economic accessibility comprise SPS, TBT measures, trade openness, income per capita, and one intra-industry trade index (HS-12); Factor 2 –Resources and policy-driven trade includes agriculture value added in GDP, simple average tariffs, terms of trade, arable land use, GL-8; Factor 3 –Inflationary pressures include temperature change on land, producer prices, agriculture trade costs, and agriculture value added per worker, Gl-17, 23; Factor 4 –Macroeconomic stability and production-driven trade contains world demand, FDI, REER, and agricultural production; Factor 5 –Trade stability and value chain consist of (GVC participation and intra-industry trade (GL Index-7, 9, commodity terms of trade stability and Factor 6 – product diversity and economic capacity includes PPP GDP, product differentiation, GL INDEX -6,10. Each factor has at least four variables. It is a sign of the replicability and strength of the factor. The factors are named based on their interrelationships and the potential competitive advantage they provide for agricultural products. In a scenario-based analysis rooted in a theoretical framework such as the new trade theory of international trade, the variables can produce a feedback loop that can determine their CA or CDA, leading to competitiveness.

Table 2: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.718
Bartlett's Test of Sphericity	Approx. Chi-Square	4693.152
	df	378
	Sig.	.000

The KMO test evaluates the appropriateness of the factor analysis for a given dataset. The KMO value in this case is 0.718, as shown in Table 2. It indicates a high validity for factor analysis. Similarly, Bartlett's test of sphericity shows significance at a 5% level. Bartlett's test of sphericity tests the null hypothesis that the correlation matrix is an identity matrix (which means unsuitability). So, the results indicate a rejection of the null hypothesis, and the model is fit. All 29 variables have shown commonalities above 0.5. It elucidates the proportion of variance that can be explained by factor analysis.

Table 3: Cointegration Results

Category	Modified Phillips–Perron t	p-value	Phillips–Perron t	p-value Dickey-Fuller t	Augmented	p-value
Cereals-BRICS	1.9808	0.0238**	-3.0391	0.0012***	-3.0019	0.0013***
Cereals-World	0.7463	0.2278	-4.9112	0.0000***	-4.0369	0.0000***

In the case of cereals, long-run cointegration exists when considering the Pedroni results at the BRICS and the world levels. In the case of Cereals in BRICS, long-run cointegration exists in Modified Phillips Perron (5%), Phillips-Perron t (1%), and Augmented Dickey-Fuller t (1%). In the world, the significance is 1% for Phillips-Perron t and Augmented Dickey-Fuller t.

Table 4: Fully Modified Ordinary Least Squares Results

India	Regulatory compliance and economic accessibility	Resources and policy-driven trade	Inflationary pressures	Macroeconomic stability and production-driven trade	Trade stability and value chain	Product diversity and economic capacity
beta_356	-1.04	1.44	-0.26	0.83	-0.48	0.35
Se._356	0.22	0.12	0.13	0.21	0.18	0.14
t-stat_356	-4.76	11.56	-1.96	3.85	-2.76	2.46
BRICS						
beta	-0.34	0.25	0.12	0.34	-0.29	0.23
t-stat	-8.05	13.24	7.37	10.19	-2.38	11.69

The F-statistics shows a fit model. The R square value is 54.9% in BRICS, then 58.75% for India in BRICS. FMOLS provided more robust estimates than other methods, such as DOLS.

The Pedroni cointegration tests have confirmed the long-run cointegrating relationship between variables in both cases. Therefore, the FMOLS method is used to identify the long-run relationship. It also helps resolve the model's endogeneity issues.

In FMOLS results, to assess the long-run relationship between the variables, for India in trade with the rest of BRICS (calculated using the Lafay index), resources and policy-driven trade factor showcased the highest significance level (11.56) (Table 6). The literature confirms the role of land use and policies in improving competitiveness (Jambor et al., 2016). The agricultural value added to GDP is considered a proxy variable for technological change. It is the highest loading variable in the resource allocation and policy-driven trade factor. An OECD paper highlighted that productivity and efficiency in agriculture are essential for enhancing competitiveness (Latruffe, 2010). It is also true that countries that experience favourable terms of trade tend to enhance competitiveness (Jambor et al., 2016). The lower trade costs due to a lenient tariffication policy would improve the terms of trade outcomes. It will create market access for cereal products (Agarwal & Betai, 2021). Therefore, it is evident from the above literature that the findings have a natural base in the existing studies.

Trade stability and value chain factors, product diversity, and economic capacity factors negatively affect Cereal's competitiveness. In FMOLS, regulatory compliance and economic accessibility have shown a negative significance (-4.76). Studies have observed that SPS and TBT measures regulate agricultural markets. While the intended purpose is often to protect food safety and integrity, these measures can also restrict trade. It can occur without a premeditated purpose or as a form of protectionism (Arita et al., 2015). The negative influence of the regulatory compliance factor (for both India and BRICS in the world in cereals, as shown in Table 6) implies higher compliance costs or difficulties in compliance, which prevents Indian producers from acquiring the benefits of economies of scale. Countries that can meet the regulatory requirements of importing markets and ensure economic accessibility for their products are more likely to be competitive in global trade (Disdier et al., 2008; Arita et al., 2015). Similarly, studies have pointed out that higher incomes are associated with greater demand for high-quality, differentiated agricultural products (Rumankova et al., 2022). Low income per capita lowers the chances of better-quality exports. The results indicate the need for more ground-level assistance for farmers, especially in overcoming trade barriers. It should ensure the ways and means to pass the regulatory barriers.

The results for BRICS generally show significance for all factors (i.e., t-statistics is above 1.96). Among these, resource and policy-driven factors are the highest, with 13.24, followed by product diversity and economic capacity factors (11.69). The recent spikes in PPT may have contributed to these favourable results for India. Regulatory compliance and economic accessibility are demonstrating a negative significance, as are trade stability and value chain factors. The literature strongly supports the influence of global value chain participation on agriculture trade competitiveness. Studies have pointed out that diversification at the extensive margins of value chains improves the terms of trade instability (Montalbano & Nenci, 2020). Therefore, BRICS should focus on more diversification. As intra-industry trade in cereals is a more important variable (highest loaded), it will likely be open to price volatility among the agri-food markets in BRICS. Therefore, efforts to reduce such price distortions or any inflationary pressures are a requirement.

Table 5: Fully Modified Ordinary Least Squares Results

India	Regulatory compliance and economic accessibility	Resources and policy-driven trade	Inflationary pressures	Macroeconomic stability and production-driven trade	Trade stability and value chain	Product diversity and economic capacity
beta India	-0.10	0.54	-0.30	0.76	0.11	-0.24
Se._ India	0.11	0.06	0.07	0.11	0.09	0.07
t-stat_ India	-0.88	8.37	-4.37	6.82	1.21	-3.22
BRICS						
beta	-0.22	-0.26	0.10	0.20	0.00	-0.08
t-stat	-4.09	-4.33	3.55	7.44	-2.88	10.35

FMOLS method for India shows that regulatory compliance, economic accessibility, trade stability, and value chain factors do not have a long-run influence. However, for BRICS, all factors exhibit significance. The third factor, inflationary pressures, shows negative and positive results for Cereals in the case of India and BRICS, respectively. A study on agricultural trade costs has shown that trade costs in agriculture limit farmers' access to international markets and consumers' access to a variety of food products at competitive prices (Beghin & Schweizer, 2021).

Macroeconomic stability facilitates trade dynamics significantly. As shown in the tables, cereals in India and BRICS experiencea positive impact. Individually and collectively, the variables impact competitiveness.

The results align well with the findings of the NTT. While specialisation and differentiation improve trade, the commodities face specific trade barriers and price volatility. The free trade agreements are a potential pathway to enable more trade creation. There is abundant trade potential to explore with countries like Russia. The product standards should follow international standardisation measures such as AEPDA and ISO 9001. The position arrived through the findings is that technological change must be a necessity so that value-added products can flourish and generate more demand. The income levels also should be raised for farmers to facilitate this transition. Therefore, the study addresses the need to invest more in research and development to promote more innovation in the agri-food sector, specifically in the case of cereals. In an era of land degradation and a rise in population, food security is a serious concern. Therefore, technological changes and different food cultivation methods, such as vertical farming, permaculture, etc, could be beneficial approaches in the future. Again, the second area of action is meeting the regulatory compliance requirements for value-added products.

Concluding Observations

The study evaluates the export competitiveness of cereals in BRICS, with a particular focus on India. Resource and policy-driven factors comprising land use, tariff structures, and value-added agriculture (AVA GDP) for cereal exports are critical. Factors like macroeconomic stability and production-driven trade (REER, World demand) also positively influence competitiveness, while regulatory compliance and economic accessibility negatively affect competitiveness, mainly through SPS and TBT measures. The findings highlight that while economies of scale and trade openness are crucial for enhancing agricultural trade competitiveness, non-tariff measures and regulatory compliance costs significantly hinder market entry. Inflationary pressures and climate-related factors further impact competitiveness. The results emphasise the need for policy interventions to reduce trade barriers, enhance specialisation, and promote sustainable resource management to improve agricultural trade outcomes.

All the findings assert the importance of land management, value-added agriculture, and diversified product offerings as drivers of trade competitiveness in cereals. Although crucial, regulatory compliance can still be a trade barrier, particularly for India. The findings unambiguously point out the role of NTMs as a distortionary trade policy. The study engaged with determinants at both the country level and firm level. To make more product-specific results, firm-level data and determinants are highly advised. Future studies should consider more disaggregate level data, especially for non-tariff measures. It is also advised to include more determinants relevant to competitiveness, such as the role of institutional factors.

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Article

Assessment of Triple Deficit Hypothesis in Selected Asian Economies: A Panel Data and Regime Switching Analysis

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Abstract

This study aims to evaluate the Triple Deficit Hypothesis (TDH) in the emerging and developing economies of the Asian region, specifically India, Bangladesh, China, Indonesia, Malaysia, and Pakistan, between 1991 and 2023. These economies lack the assessment of the TDH in these regions. Both fiscal balance and saving investment gaps have been found to be highly significant variables, where the current account can be improved by regulating fiscal deficit and increasing domestic savings. In contrast, the real effective exchange rate negatively affects the current account balance

Keywords: Triple deficit hypothesis; Emerging and developing economies, Panel data analysis, Markov-switching model

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Introduction

The pursuit of macroeconomic stability and sustained economic growth in countries primarily relies on fiscal discipline and the current account (Lau et al., 2010; Fatima et al., 2011; Udoh, 2011). This is why the relationship between fiscal deficit (FD) and current account deficit (CAD) has been emphasised over time. The persistent FD and CAD could extend beyond the nation's boundaries, leading to global financial instability and perhaps an economic crisis (Mendoza et al., 2007). These would severely impact our future generations. Furthermore, they might deter prospective foreign investors and donors, as they indicate an unstable economy, which would surely affect the growth rate (Sayki et al., 2016).

Historically, the Twin Deficit Hypothesis (TwDH) analyses the connections between a nation's internal fiscal position and its external account. It posits that fiscal deficits often cause current account deficits. Such a perspective is supported by numerous studies, arguing that expansionary fiscal policies can increase imports and reduce national savings, thereby worsening the current account. However, with the rising integration globally, it is difficult to capture the complexities of macroeconomic dynamics following TwDH fully. The Triple Deficit Hypothesis (TDH), as expounded in Akbas et. al. (2014), expands the twin deficit model, incorporating the savings-investment (S-I) gap as a third key variable. Here all the three exhibit simultaneous imbalance. It says that one of the major causes of the deterioration of a country's current account is its consistently high domestic investment exceeding its savings. This holistic strategy is relevant for developing economies, which often face low savings rates and substantial investment demands.

Despite its theoretical relevance, there has been limited evidence of empirical research on the TDH in the context of developing Asian economies. The studies are mostly centred around individual countries or developed regions, so there is a lack of comparative and cross-country analysis in the Asian region. Furthermore, recent studies rely on linear or static econometric approaches that do not incorporate structural changes or shifts in economic regimes, specifically during crises.

The study aimed to test the TDH across six Asian countries empirically from 1991 to 2023. Advanced panel data methodologies have captured long-term relationships and structural shifts, including cointegration analysis, long-run estimators such as FMOLS and DOLS, and a Markov Switching Regression model.

The focus is on key macroeconomic variables while acknowledging the exclusion of institutional and political dimensions due to data limitations. The study contributes to the existing literature by offering cross-country evidence from Asia, using methods beyond linear assumptions, and providing insights with practical policy relevance.

The remaining part of the paper is organisedas follows. Section 2 provides an overview and analysis of the existing theoretical and empirical research. Section 3 provides an overview of the theoretical foundation and addresses the approach used for empirical analysis. Section 4 provides a detailed methodology and examination of the data. Section 5 gives a thorough discussion of the empirical findings. Section 6 presents as the conclusion and policy recommendations.

Literature Review

According to Keynesian economic theory (Bernheim, 1988; Abell, 1990), fiscal imbalance deteriorates the country's trade position as import demand increases. The Ricardian Equivalence Hypothesis (Barro, 1974) however holds that because people can anticipate future tax rises that will pay off the public debt, they will increase their savings in order to act upon the impacts of government borrowing upon the current account.

Other factors, such as the saving-investment gap, have been highlighted by more recent changes in the global economy. TwDH mainly focuses on the association of FD with CAD. It is observed that country's current account imbalances decline as national savings trail domestic investment often. This is frequently funded by foreign capital. This funding creates disparity. Accordingly, imbalances in a country's current account worsen when domestic investment regularly outpaces national savings. Given economies are increasingly open, it is important to understand how capital flows and savings behaviour impact external balances, particularly in the developing world, according to scholars like Feldstein (2008) and Fischer and Easterly (1990).

The empirical research examining these linkages have comeup with conflicting finding. While evidence of a two-way interaction was found by Darrat (1988) and Alam et al.

(2014), Anoruo and Ramchander (1998) and Marinheiro (2008) found evidence of one-way causal relationship. Ricardian neutrality is supported in some of the research and holds that fiscal deficits can have little effect upon the external balance. This is especially true in developed countries such as the United States (Kim & Roubini, 2008).

The growing literature for the TDH is still in its early stages. A strong correlation exists between the S-I gap and Turkey's CAB according to Akbaş et al. (2014). Fiscal balance was observed to be correlated strongly too. Akbaş and Lebe (2016) noted trends like these in, as did Bolat et al. (2014) throughout the EU. These findings do support applicability for TDH while also emphasising the potential for these associations to change during emergencies.

Yet, studies on TDH regarding Asian developing countries are still limited. Shastri et al. (2017) studied this issue in South Asia, though they left out regime transitions plus structural breaks. Sahoo and Das (2012) studied this in India, and Fatima et al. (2011) focused on Pakistan. These studies examined twin deficits using linear models. However, these model models disregarded macroeconomic shocks plus external competitiveness like the Real Effective Exchange Rate (REER) and financial crises. The literature covers developed economies and still has conceptual as well as methodological gaps. The policy implications are often insufficiently applicable for general use.

Theoretical Framework

Theoretically, the analysis of the relationship between fiscal and current account balance can be derived from the national income identity for an open economy-

$$CAB = S - I = (T - G) + (Y - C - T) - I$$

The equation implies that the current account balance is the sum of public savings (fiscal balance) and private savings minus investment. According to the Keynesian view, in an open economy, current account deficits can be caused by high capital mobility and fiscal deficits (Bernheim, 1988; Abell, 1990). The Ricardian Equivalence Hypothesis (Barro, 1974) focuses on a neutral effect, rarely found in developing economies.

The TDH is an extension of the TwDH. S-I Gap is included as the third variable in the model. A persistent increase in investment over domestic savings implies dependence on foreign capital, thereby widening the CAD (Fischer & Easterly, 1990; Feldstein, 2008). The primary explanatory variables are FB and S-I Gap. The REER is added as a control, reflecting trade competitiveness. Furthermore, the Economic crisis is the dummy variable that captures external shocks.

Methodology and Data

Panel data methods plus Markov-Switching models are used in the present study to examine the TDH in six major Asian economies: Bangladesh, China, Indonesia, Malaysia, Pakistan, and India. This study incorporates variables like REER and considers global downturns.

The following model is used in the study:

$$CAB_{t,i} = \beta_0 + \beta_1 FB_{t,} + SI_{t,i} + REER_{ti} + Cr_{ti} + U_{t,i}$$

where CAB implies the Current Account Balance, FB is the government's Fiscal Balance, and SI is the private Saving-Investment Gap, REER represents the Real Effective Exchange Rate as suggested in El-Khishim and Saeed (2021), and Cr represents the economic crisis period. All three variables, namely CAB, FB, and S-I Gap, are expressed as a percentage of GDP, following standard practice. The REER is taken on the Consumer Price Index, and the data is taken from the Bruegel Working Paper (Darvas, 2012). The data on CAB are sourced from World Development Indicators, whereas data for FB and S-I Gap are collected from the World Economic Outlook Report of the IMF. The data for the S-I Gap for different sample countries were unavailable. Thus, it is calculated by taking the difference between gross national saving and gross capital formation.

The Levin-Lin Chu (LLC) and Im-Pesaran (IPS) tests assess the data's stationarity properties at both the levels and the first difference.

$$\Delta y_{it} = a_i + \beta_i y_{i,t-1} + \sum_{j=1}^{p} \gamma_{ij} \Delta y_{i,t-j} + \varepsilon_{it}$$

where, y_{it} denotes the dependent variable for cross-section i at time t, a_i signifies individual-specific fixed effects, β_i is the coefficient of the lagged dependent variable for unit root testing, γ_{ij} represents the coefficients of lagged first differences of , is the error term, and p indicates the number of lags chosen. The hypothesis test posits H_0: All series exhibit unit roots (=0 for all i) and H_1: Some (though not necessarily all) series are stationary (<0 for at least some i). In the LLC test, the null and alternative hypotheses are defined as H_0: All series contain unit roots (= 0) and H_1: All series are stationary (β< 0).

To examine the existence of a long-term link, we conduct first- and second-generation panel cointegration tests as proposed by Pedroni (1999) and Westerlund (2007). The equation proposed by Pedroni (1999) is as follows:

$$Y_{it} = \alpha_i + \delta_i t + \beta_1 x_{1it} + \beta_2 x_{2it} + \ldots\ldots\ldots + \beta_k x_{k,it} + \varepsilon_{it}$$

where, Y_{it} is the dependent variable for cross-section i at time t, $x_{k,it}$ are the explanatory variables, α_i represents individual-specific fixed effects, $\delta_i t$ allows for deterministic time trends, β_k are the long-run cointegration coefficients, and ε_{it} is the residual term. If the residuals ε_{it} are stationary, then the variables are cointegrated.

$$\Delta y_{it} = \alpha_i + \delta_i t + \lambda_i(y_{i,t-1} - \beta 2_I\, x_{i,t-1}) + \sum_{j=1}^{p} \gamma_{ij} \Delta y_{i,t-j} + \sum_{j=0}^{p} \delta_{ij} \Delta x_{i,t-j} + \varepsilon_{it}$$

where, represents the dependent variable for cross-section i at time t, $x_{i,t}$ are the explanatory variables, α_i represents individual-specific fixed effects, $\delta_i t$ is the deterministic trend, λ_i is the error correction term, which measures how quickly deviations from equilibrium are corrected, capture short-run dynamics, ε_{it} is the error term, p implies the number of lags. The test examines if λi<0, indicating that the system returns to equilibrium. The null hypothesis (H0) posits the absence of cointegration (λi=0 for all i), while the alternative hypothesis (H1) asserts the presence of cointegration.;Panel statistics: λi<0 for all i (homogeneous cointegration); and Group statistics: λi<0 for at least some i (heterogeneous cointegration).

The econometric strategy aligns with the theoretical framework of the TDH. To verify whether the series of variables fit long-run modelling, panel unit-root tests (LLC, IPS) are done. In line with the theoretical expectations of equilibrium relationships, we evaluated the existence of a stable long-run relationship among the variables following the cointegration tests. In case of weak or absent cointegration, FMOLS and DOLS estimators obtain consistent long-run coefficients, addressing the endogeneity and autocorrelation. To examine directional influences, consistent with the hypothesis that fiscal and savings behaviour impact the current account, Dumitrescu-Hurlin panel causality tests are employed. Lastly, the Markov-Switching model is applied, incorporating the theory's argument for regime shifts during crises, to estimate dynamic relationships between stable periods and economic distress.

Empirical Analysis

Table 1: Results of Panel Unit Root Tests

H_0: series has a unit root	Levels		First Difference	
H_1: Series has no unit root	*p*-Value		*p*-Value	
	LLC	IPS	LLC	IPS
CAB	0.0983	0.0214	0	0
FB	0.085	0.2158	0	0
SI Gap	0.0287	0.0037	0	0
REER	0.1593	0.449	0	0

Source: Authors' estimates.
Note: The unit root for the crisis variable has not been checked due to insufficient observations.

The results of the panel unit root tests, derived from the LLC and IPS methodologies, indicate mixed evidence regarding stationarity in levels but strong evidence of stationarity after first differencing. At levels, the null hypothesis of a unit root cannot be rejected for the majority of variables at the 5% significance threshold, except for the S-I Gap (p-values: LLC = 0.0287, IPS = 0.0037) and, to a lesser extent, the CAB (IPS = 0.0214). The FB and REER exhibit higher p-values in levels, indicating non-stationarity. However, after applying the first difference, all variables become stationary with p-values of 0.000 across both tests, indicating that these series are integrated of order one, i.e., I(1). This finding supports using first differences in further econometric analyses to avoid spurious results.

Table 2: Results of Pedroni's Cointegration Test

Panel cointegration (within dimension	Statistics
panel V-statistic	0.6881
panel rho-statistic	-1.174
panel t-statistic	-1.689
panel ADF-statistic	-0.3955
GM (between dimension)	
Group rho-statistic	-0.7774
Group t-statistic	-1.822
Group ADF-statistic	-0.08439

Source: Authors' estimates.

Table 3: Results of Westerlund Cointegration Test

Statistic	Value	z-value	*p*-Value
Gt	-1.199	0.426	0.665
Ga	-3.057	1.239	0.892
Pt	-2.572	-0.208	0.418
Pa	-1.988	0.255	0.601

Source: Authors' estimates.

The findings of Pedroni's panel cointegration test yield inconclusive evidence concerning a long-term relationship among the variables. Within-dimension statistics shows that the panel V-statistic (0.6881) is insignificant, suggesting no cointegration. However, the panel rho-statistic (-1.174) and panel t-statistic (-1.689) are more supportive of cointegration, though the panel ADF-statistic (-0.3955) is not significant enough to confirm it. In the between-dimension (group) statistics, the group rho-statistic (-0.7774) does not provide strong evidence of cointegration, but the group t-statistic (-1.822) indicates potential long-run relationships. The group ADF-statistic (-0.08439) is also not significant. Overall, the results suggest weak and inconsistent evidence of cointegration, indicating that the variables may possess a long-term relationship, although the data lacks robustness across all statistical tests.

The findings of Westerlund's panel cointegration test reveal no substantial evidence of a long-term equilibrium relationship among the variables. The assessment yields four statistics: GtG_t, GaG_a, PtP_t, and PaP_a. All p-values exceed the 5% significance threshold, signifying that the null hypothesis of no cointegration cannot be refuted. Specifically, the GtG_t statistic (-1.199) has a p-value of 0.665, the GaG_a statistic (-3.057) has a p-value of 0.892, the PtP_t statistic (-2.572) has a p-value of 0.418, and the PaP_a statistic (-1.988) has a p-value of 0.601. The results indicate that the variables lack a stable long-term relationship, reinforcing the conclusion that the series is likely not cointegrated during the panel period.

Table 4: Long-run Coefficients under Alternative Estimators

Variables	DOLS		FMOLS	
	Coefficient	*p*-Value	Coefficient	*p*-Value
FB	-0.285	0.0711	-0.2599	0.0047
SI Gap	0.668	0	0.6427	0
REER	-0.063	0	-0.0553	0
Economic Crisis	0.129	0.9018	-0.1326	0.7436

Source: Authors' estimates.
Note: Dependent variable – CAB.

Within the TDH context, the estimation findings from the FMOLS and DOLS models shed light on the connections between the current account balance and its possible drivers. Both models yield consistent findings, particularly for the FB, S-I Gap, and REER. The FB shows a negative relationship with the CAB, with a statistically significant coefficient in the FMOLS model (-0.2599, p = 0.0047), supporting the hypothesis that a declining fiscal balance correlates with a worsening current account deficit. The S-I Gap exhibits a strong positive and highly significant relationship across both models (DOLS: 0.668, FMOLS: 0.6427; p = 0.000), suggesting that higher domestic savings relative to investment improve the CAB. The REER has a negative and significant effect (DOLS: -0.063, FMOLS: -0.0553; p = 0.000), indicating that an appreciation of the domestic currency worsens the CAB by reducing external competitiveness. The economic crisis variable is insignificant in both models, indicating no noticeable effect on the current account over the investigated period. The findings offer modest validation for the TDH, highlighting the significant role of the FB and the S-I Gap in influencing the CAB.

Table 5: Results of Dumitrescu-Hurlin Panel Causality Test

Null Hypothesis	W-Stat.	Zbar-Stat.	*p*-Value
FB does not homogeneously cause CAB	0.78163	-1.43483	0.1513
CAB does not homogeneously cause FB	2.48449	0.31121	0.7556
SI_Gap does not homogeneously cause CAB	1.87526	-0.30979	0.7567
CAB does not homogeneously cause SI_Gap	6.75199	4.71478	2.00E-06
REER does not homogeneously cause CAB	5.94684	3.88523	0.0001
CAB does not homogeneously cause REER	0.91578	-1.29835	0.1942
Crisis does not homogeneously cause CAB	4.27645	2.1642	0.0304
CAB does not homogeneously cause Crisis	2.26226	0.08895	0.9291
SI_Gap does not homogeneously cause FB	2.95484	0.8104	0.4177
FB does not homogeneously cause SI_Gap	1.82665	-0.35709	0.721
REER does not homogeneously cause FB	3.38003	1.25041	0.2111
FB does not homogeneously cause REER	3.14123	1.00329	0.3157
Crisis does not homogeneously cause FB	7.84563	5.87159	4.00E-09
FB does not homogeneously cause Crisis	1.43194	-0.76555	0.4439
REER does not homogeneously cause SI_Gap	4.89385	2.8361	0.0046
SI_Gap does not homogeneously cause REER	1.4732	-0.72116	0.4708
Crisis does not homogeneously cause SI_Gap	4.9953	2.94161	0.0033
SI_Gap does not homogeneously cause Crisis	0.73115	-1.49285	0.1355
Crisis does not homogeneously cause REER	2.94931	0.81391	0.4157
REER does not homogeneously cause Crisis	3.82097	1.72038	0.0854

Source: Authors' estimates.

In the complex interactions among FB, SI_Gap, REER, CAB, and economic crises in the selected Asian economies, some notable insights have been found with the help of the Dumitrescu-Hurlin panel causality test. The TDH posits that there are interconnections among FB, private S-I Gap, and CAB. However, the results offer limited support to the hypothesis.

The results do not confirm a homogeneous causal relationship from fiscal balance to the current account balance (p = 0.1513) or vice versa (p = 0.7556), contrary to the findings of Akbaş et al. (2014) for Turkey and Shastri et al. (2017) for South Asia. The finding contradicts those studies where fiscal policy is found to determine the current account outcomes, particularly under the Keynesian framework. The reasons for such differences can be different periods, policy responses, and the nature of fiscal deficits in the observed countries. For instance, India and Bangladesh adopted a countercyclical fiscal policy post-2008, which may have diluted the direct transmission from fiscal deficits to external imbalances.

Again, in the interaction between S-I Gap and CAB, the results contradict those of Feldstein (2008) and Akbaş and Lebe (2016)**,** who emphasised the key role of domestic saving-investment dynamics in explaining current account trends. An interesting finding is the significant reverse causality from the CAB to the SI_Gap (p = 2.00E-06), indicating that CAB may be influencing domestic saving and investment patterns rather than the other way around. It can be said that the domestic investment decisions and savings behaviour are altered by capital flow reversals or trade shocks, especially in periods like the 2008 global financial crisis or the COVID-19 pandemic.

Supporting the findings of Kim and Roubini (2008), a strong unidirectional causality is found from REER to CAB (p = 0.0001), confirming that exchange rate fluctuations significantly impact trade balance. Further, Economic Crisis is found to have a significant causal influence on both the CAB (p = 0.0304) and the SI_Gap (p = 0.0033), highlighting the role of exogenous shocks in determining internal and external imbalances, supporting the findings of Bolat et al. (2014) for the EU and crisis-prone regions.

In conclusion, though the findings contradict traditional TDH expectations regarding the fiscal-external link, an important contextual nuance is highlighted that in developing Asian economies, external shocks and exchange rate fluctuations may exert a more dominant impact on macroeconomic balances than fiscal policy alone. The study stresses the necessity of accounting for crisis effects and structural heterogeneity in the presence of TDH across diverse economic environments.

The findings from the Markov-Switching Dynamic Regression model, computed for the period 1991–2023, provide substantial insights into the relationship between CAB and important macroeconomic indicators in the case of the selected countries of the study. The two regimes are identified by the model where Regime 1 (S(t)=1) is characterised bya Stable or Low-Deficit Period, whereas Regime 2 (S(t)=2) features a Crisis or High-Deficit Period. Regime 1 would represent stronger economic fundamentals with a smaller current account deficit/surplus, lower fiscal deficits, a more balanced saving-investment gap, and stable exchange rates. When P(S(t)=1) is high (close to 1) for a long period, it reflects the macroeconomic stability of the economy. Regime 2 would depict a phase of macroeconomic distress where there would be a widening of CAD, high FD, worsening of S-I Gap, and exchange rate volatility. When P(S(t)=2) is high (close to 2), it means the country is experiencing a phase of fiscal and external instability.

In the case of India (Figure 1.1), from 1995 to 2003, P(S(t)=1) is high, suggesting a relatively stable fiscal and external balance in this period; this means that India experienced a moderate deficit during this period, with some impact of the 1997 Asian Financial Crisis. The period between 2004 and 2013 registers a rise in P(S(t)=2), where India moved into a deficit crisis regime. This period saw a high fiscal deficit and rising current account imbalances. The likely root cause of this phase may be the 2008 global financial crisis, where external shocks led to capital outflows. During 2014 - 20, P(S(t)=1) dominated again, where the CAD narrowed down due to policy reforms taken by the government and fiscal adjustments made. However, the whole world was highly impacted by COVID-19 pandemic, but here, in the case of India, it may have briefly impacted the stability. Following 2014, the economy appears to regain stability, and the findings indicate a high overall probability of remaining in Regime 1.

Figure 1.1 India

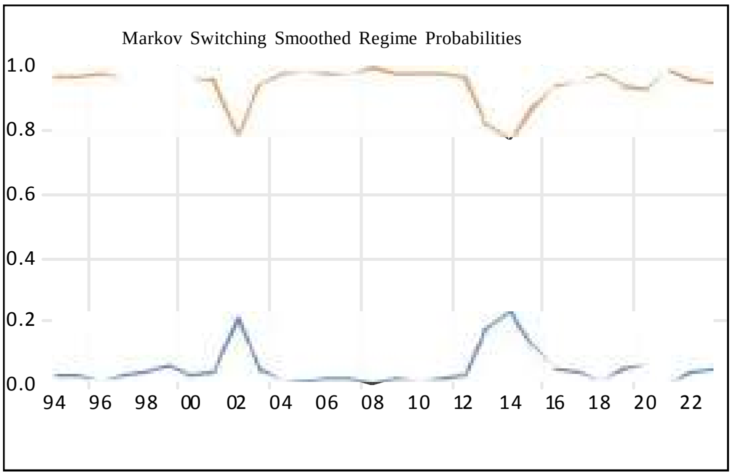
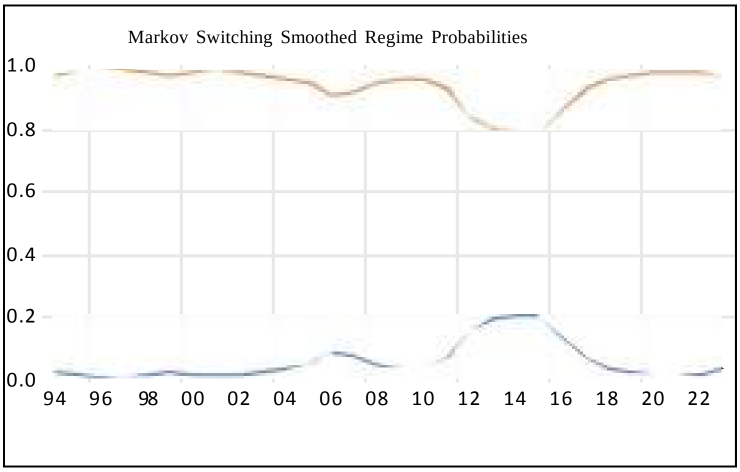


Figure 1.2 Bangladesh



Source: Authors' estimates.

Figure 1.2 represents the case of Bangladesh. The regime (1995-2005) is a stable period with P(S(t)=1) close to 1, where the deficits are manageable due to the export-led growth, the high inflow of remittances, and a relatively balanced fiscal and current account position. Regime 2, from 2006 to 2014, marks the shift between regimes, depicting a macroeconomic distress period. With the rise, the economy transitions towards a deficit crisis period, possibly due to the 2008 global financial crisis; however, in the literature, the Bangladesh economy seems to be less impacted by the crisis, with rising fiscal deficits as can be traced from Appendix Table 1 and the rise in CAD due to a surge in imports. Regime 1 dominated again during 2015-20, indicating a more stable period due to the policies framed to curb fiscal deficit, with stronger remittances inflow and export diversification leading to improved external sector performance.

Figure 1.3 represents the case of the Chinese economy. The period of analysis starts from 2000 due to the adjustment made to the model. The period from 2000 to 2008, Regime 1, is a stable period characterised by strong macroeconomic stability in the economy, where China experienced high current account surpluses, a better fiscal position, and a rising saving-investment balance. The boom in this period is probably due to the rapid industrialisation and global trade expansion in the economy. Then, 2008-2010 shows a transition to Regime 2, where economic downturn or fiscal stress is noticed. The global financial crisis severely impacted the Chinese economy, resulting in a decrease in exports and foreign investment, and there was large-scale government spending, which led to a rise in fiscal deficits. The period 2011-18 again witnessed Regime 1, and the economy returned to stability, due to the recovery from the crisis. There was another shift to Regime 2 between 2019 and 2022, where COVID-19 and the US-China trade war hit the economy. As per the analysis, the economy is expected to transit again to Regime 1.

Figure 1.3 China

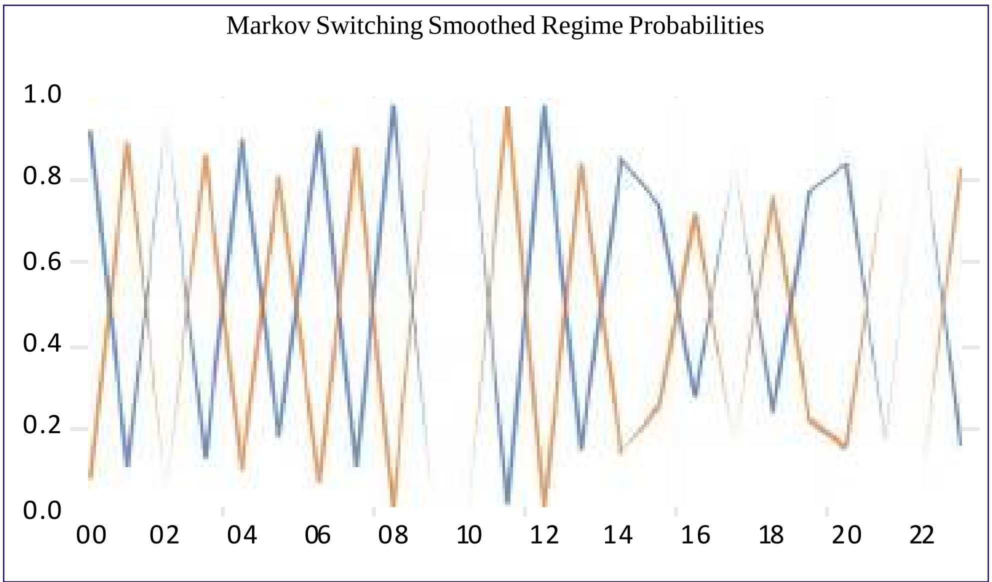
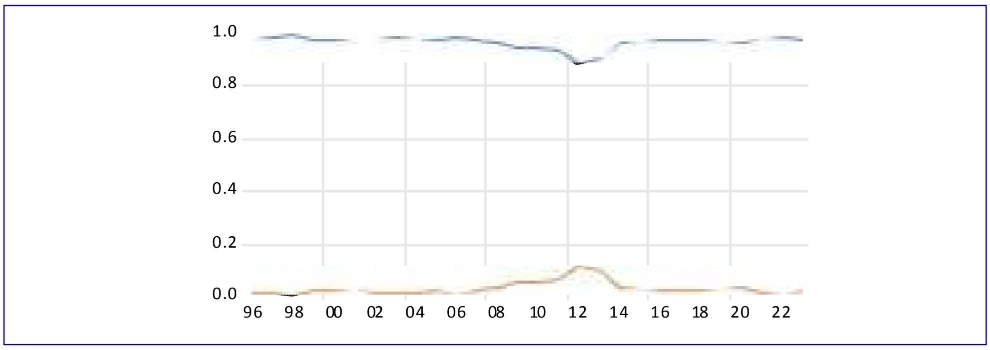


Figure 1.4 Indonesia

Markov Switching Smoothed Regime Probabilities



Source: Authors' estimates.

The case of the Indonesian economy is depicted in Figure 1.4. The period between 1996 and 1999 was predominantly that of an economic crisis, in which the economy was in Regime 2. The period aligns with the 1997 Asian Financial Crisis. Then it transits to Regime 1 between 2000 and 2008, and the drivers of stability could be improved fiscal management, strong export growth, stable exchange rates, and economic reforms taken. Then there was a temporary shift in Regime 2 between 2008 and 2010, and that was due to the global financial crisis. From 2011 to 2018, the period witnessed prolonged stability where Regime 1 dominated again, and the period registered higher GDP growth, improved fiscal disciplines, and manageable CAD. Then it again shifts back to Regime 2 between 2019 and 2022, due to the COVID-19 pandemic.

Figure 1.5 Malaysia

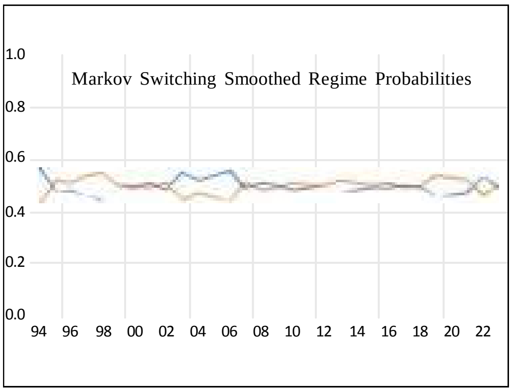
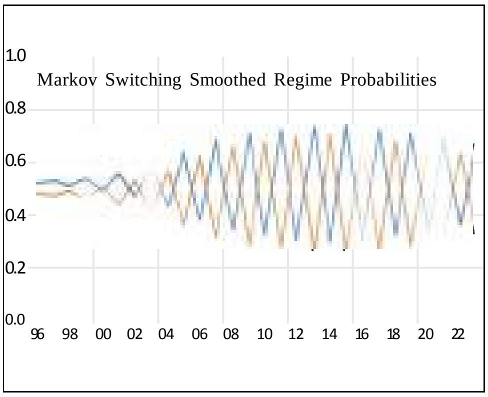


Figure 1.6 Pakistan



Source: Authors' estimates

In the case of Malaysia (Figure 1.5), the economy was stable between 1994 and 1997, a Regime 1 condition, where the Malaysian economy experienced high growth, low FD, and CAD. The economy witnessed a transition to Regime 2 between 1997 and 2001, caused by the Asian Financial Crisis, leading to currency depreciation, capital outflows, and high FD. Then stability was restored and the economy shifted back to Regime 1 between 2000 and 2008 due to the export-led growth, fiscal consolidation, and manageable CAB. There was another shift to Regime 2 during 2008-2010 amid the Global Financial Crisis. The period from 2011 to 2019 marks sustained stability, but the period from 2019 to 2022 shifted back to Regime 2 again due to the COVID-19 pandemic. Due to the frequent transitions between the regimes, it can be said that the economy is prone to remaining in Regime 2.

As far as the case of Pakistan is concerned (Figure 1.6), the economy faced an economic crisis from 1996 to 1999, Regime 2 due to the balance of payment crisis in 1999. It then transitioned to Regime 2 due to the help from the IMF in the name of structural reforms. Regime 2 was again restored between 2008 and 2010 due to the Global Financial Crisis. The period between 2011 and 2016 is a period of recovery and stability, which could be due to the China-Pakistan Economic Corridor (CPEC). Due to the rising FD and external debt burden, the economy shifted back to Regime 2 (2017-2022). The other possible reasons could be currency depreciation, the COVID-19 pandemic and political instability. The economy is more likely to shift back to Regime 1.

This study enhances its approach by incorporating Markov-Switching analysis, which offers substantial benefits compared to conventional linear methods found in previous TDH literature. In contrast to static panel or time-series models that presume unchanging relationships over time, the Markov-Switching framework effectively captures nonlinear dynamics and behaviour that depend on different regimes. This allows for transitions between periods of macroeconomic stability and crisis. Such a framework is especially pertinent for developing Asian economies that often face external shocks and changing policies.

The results indicate that these economies shifted between high-deficit (crisis) and low-deficit (stable) states during critical economic situations, such as the 1997 Asian Financial Crisis, the 2008 Global Financial Crisis, and the COVID-19 pandemic. For instance, the correct policy reform measures helped India and China regain stability after the crises, whereas Pakistan and Malaysia experienced extended periods of vulnerability. The study's broader conclusion highlights that the macroeconomic imbalances in such regions are still unfixed and that the effectiveness of policies should be interpreted within the context of changing economic regimes.

Concluding Observations

In this study, the validity of the TDH is examined in six key Asian economies of India, Bangladesh, China, Indonesia, Malaysia, and Pakistan for the period 1991 to 2023. A set of panel data was analysed using econometric methods, such as FMOLS, DOLS, Dumitrescu-Hurlin panel causality tests, and Markov-Switching models to capture both long-term relationships and regime-specific variations among FB, CAB, SI, and REER. The study extends partial empirical support for the TDH. It is found that there are significant effects of the S-I gap and REER on the CAD; however, the fiscal balance and external balance do not have the expected strong causal relationship between them. The inadequacy of static models is observed by the Markov-Switching models, which reveal that macroeconomic behaviour varies across stable and crisis periods.

On the basis of these findings, several concrete policy recommendations may be made. First, to reduce deficits during the boom period, the government must strengthen countercyclical fiscal measures and establish targeted stimulus during downturns. This may include adopting fiscal responsibility laws, multi-year budget plans, and advancing expenditure quality. Second, there is a need to reduce the savings-investment gap. Thus, household and corporate savings should be incentivised via tax benefits, encouraging financial inclusion, and more inclusivity through social security, specifically in the informal sectors. Simultaneously, high-yield sectors such as infrastructure, digital economy, and green energy should be the targeted areas for investment, which will reduce the reliance on foreign capital and boost long-term external balances. Third, the study's findings indicate that REER is a significant variable, which means that exchange rate management is important. A managed float regime should be adopted to preserve export competitiveness. Fourth, it is important to institutionalise crisis preparedness. Fiscal buffers, prudent debt management, and structural reforms should be implemented to improve the resilience of countries to global shocks.
The existence of regime shifts indicates the requirement for the development of

macroeconomic early warning systems. Tools designed to alertpeople about real-time indicators and scenario modelling would facilitate timely fiscal and monetary action, especially during external or internal stress periods.

The study has some limitations. The focus is primarily on six Asian economies, and due to data limitations, the other potentially influential factors, such as institutional quality, political stability, and sectoral investment patterns, are omitted. Also, a uniform regime-switching behaviour across time is considered, which may oversimplify dynamic transitions. The scope for future research can include a broader set of countries and integrate institutional and governance variables. Further, there is a scope for exploring sector-specific effects and interaction mechanisms that enhance the understanding of how triple deficits evolve across different macroeconomic contexts.

The study contributes to the existing TDH literature by introducing a regionally focused, empirically rigorous, and policy-relevant view. Integrating nonlinear dynamics and regime-switching analysis offers noteworthy insights for academics, policymakers, and researchers who aim to design more resilient macroeconomic frameworks in developing economies.

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Appendix

Table 1: Trends of Current Account Balance, Fiscal Balance, and S-I Gap for Selected Countries

Year	India			Bangladesh			China			Indonesia			Malaysia			Pakistan		
	CAB	FD	S-I Gap	CAB	FD	S-I Gap	CAB	FD	S-I Gap	CAB	FD	S-I Gap	CAB	FD	S-I Gap	CAB	FD	S-I Gap
1991	-1.59	-7.76	-0.43	-1.52	0.52	2.74	-	-1.04	-3.73	-3.65	-	-19.93	-8.51	1.60	-11.06	-2.78	-	-2.90
1992	-1.56	-7.76	-1.68	-0.55	0.42	1.96	-	-1.22	0.69	-2.17	-	-17.73	-3.66	1.81	-6.96	-3.84	-	-1.68
1993	-0.67	-8.42	-0.41	-0.30	0.50	-0.18	-	-0.90	1.15	-1.33	-0.59	-6.61	-4.47	3.44	-7.86	-5.60	-6.90	-4.99
1994	-0.51	-7.86	-1.01	-0.49	0.04	0.16	-	-1.69	-3.14	-1.58	0.41	-7.06	-6.07	5.45	-10.50	-3.47	-4.53	-2.45
1995	-1.54	-6.70	-1.61	-1.19	-0.44	-0.13	-	-0.95	-2.92	-3.18	0.64	-8.49	-9.74	3.10	-8.93	-5.52	-4.87	-2.74
1996	-1.52	-6.59	-1.13	-1.72	-2.38	-0.22	-	-0.74	-3.39	-3.37	0.96	-8.63	-4.42	3.27	-4.06	-7.01	-5.41	-5.04
1997	-0.71	-8.13	-1.30	-1.44	-2.28	0.41	3.84	-0.73	-3.86	-2.27	-1.03	-7.27	-5.93	4.84	-5.44	-2.74	-4.83	-4.41
1998	-1.64	-9.58	-0.94	-0.55	-2.57	-0.35	3.06	-1.09	-3.07	4.29	-1.89	-2.21	13.20	-0.63	12.12	-3.61	-5.57	-2.10
1999	-0.70	-8.55	-1.01	-0.57	-1.56	-0.41	1.93	-2.32	-1.94	4.13	-0.96	-1.16	15.92	-3.00	14.62	-1.46	-3.83	-2.41
2000	-0.98	-8.26	-0.56	-0.55	-2.92	-0.50	1.69	-2.85	-1.70	4.84	-1.87	-0.18	9.05	-6.05	8.31	-0.10	-4.01	-0.27
2001	0.29	-10.84	0.69	-1.63	-4.08	-1.18	1.30	-2.60	-1.31	4.30	-1.76	-0.64	7.85	-6.36	7.21	2.36	-3.06	0.42
2002	1.37	-10.88	1.21	0.24	-2.74	-0.49	2.41	-2.88	-2.42	4.00	-0.38	-0.86	7.13	-5.96	7.31	4.82	-3.31	3.62
2003	1.44	-11.23	2.28	0.25	-2.34	0.48	2.59	-2.39	-2.60	3.45	-1.08	-1.38	12.14	-6.60	10.77	3.89	-0.15	4.53
2004	0.11	-9.06	-0.34	0.23	-2.62	0.41	3.53	-1.51	-3.54	0.61	-0.26	-3.36	12.09	-5.35	11.10	-0.76	-1.62	1.74
2005	-1.25	-7.37	-1.19	-0.70	-2.85	0.26	5.79	-1.40	-5.78	0.10	0.42	-5.01	13.92	-2.83	13.76	-3.00	-2.81	-1.25
2006	-0.99	-6.32	-1.01	0.67	-2.57	1.69	8.42	-1.14	-8.42	2.98	0.37	-3.22	16.10	-2.60	15.36	-4.92	-3.29	-3.57
2007	-0.66	-4.51	-1.27	1.00	-2.23	1.71	9.95	0.06	-9.93	2.43	-0.95	-4.38	15.38	-2.57	14.66	-5.45	-5.12	-4.44
2008	-2.58	-8.98	-2.28	0.25	-4.03	1.59	9.15	-0.02	-9.19	0.02	0.05	0.02	16.86	-3.41	16.29	-9.20	-7.06	-8.12
2009	-1.95	-9.53	-2.82	1.70	-3.21	2.40	4.77	-1.75	-4.78	1.97	-1.64	1.84	15.72	-3.88	14.83	-2.37	-5.05	-5.54
2010	-3.25	-8.63	-2.80	2.35	-2.68	3.20	3.91	-0.36	-3.94	0.68	-1.24	0.70	10.06	-4.32	9.94	-0.76	-6.01	-2.23

2011	-3.48	-8.35	-4.19	-1.45	-3.59	1.46	1.80	-6.10	-1.82	0.19	-0.70	0.19	10.90	-3.57	10.74	-1.03	-6.73	0.10
2012	-5.00	-7.55	-4.81	-0.28	-2.98	1.59	2.52	-6.30	-2.52	-2.66	-1.59	-2.66	5.19	-3.10	5.09	-1.04	-8.63	-2.09
2013	-2.65	-7.00	-1.74	1.33	-3.38	2.14	1.55	-6.84	-1.54	-3.19	-2.22	-3.18	3.47	-3.48	3.44	-1.91	-8.37	-1.08
2014	-1.34	-7.07	-1.31	0.68	-3.08	0.65	2.25	-6.88	-2.24	-3.09	-2.15	-3.09	4.39	-2.63	4.33	-1.50	-4.85	-1.28
2015	-1.07	-7.21	-1.05	1.23	-3.98	0.13	2.65	-2.79	-2.64	-2.04	-2.40	-2.04	3.01	-2.55	2.99	-1.04	-5.25	-1.04
2016	-0.53	-7.12	-0.63	1.61	-3.36	1.61	1.70	-3.70	-1.70	-1.82	-2.49	-1.82	2.37	-2.60	2.39	-2.58	-4.42	-1.78
2017	-1.44	-6.23	-1.84	-0.45	-3.34	-0.87	1.53	-3.84	-1.54	-1.59	-2.51	-1.60	2.81	-2.41	2.79	-5.31	-5.76	-4.03
2018	-2.43	-6.38	-2.12	-2.58	-4.64	-3.82	0.17	-4.66	-0.18	-2.94	-1.75	-2.94	2.24	-2.65	2.23	-6.00	-6.42	-6.13
2019	-1.04	-7.39	-0.86	-1.28	-5.43	-2.07	0.72	-6.34	-0.72	-2.71	-2.23	-2.70	3.50	-2.22	3.50	-3.07	-8.96	-4.85
2020	1.23	-12.78	0.90	-1.45	-5.54	-1.80	1.86	-11.18	-1.84	-0.42	-5.87	-0.42	4.26	-5.18	4.24	0.09	-8.04	-1.70
2021	-1.46	-9.27	-3.54	-1.10	-3.56	-5.68	1.99	-6.05	2.94	0.30	-4.41	3.68	3.89	-6.03	7.23	-3.52	-6.04	-8.93
2022	-2.36	-9.20	-4.66	-3.95	-4.12	-6.82	2.48	-7.51	3.41	1.00	-2.19	9.52	3.19	-4.81	7.19	-3.26	-7.84	-11.95
2023	-0.90	-8.32	-4.05	-2.58	-4.58	-5.19	1.43	-6.95	2.28	-0.16	-1.61	7.61	1.55	-4.55	5.10	-0.24	-7.72	-7.64

Source: World Development Indicators; *World Economic Outlook*

Declarations

A) Data Sources
1) World Development Indicators (https://databank.worldbank.org/source/world-development-indicators#)
2) IMF World Economic Outlook Database (https://www.imf.org/en/Publications/SPROLLs/world-economic-outlook-databases#sort=%40imfdate%20descending)
3) IMF International Finance Statistics (https://data.imf.org/?sk=4c514d48-b6ba-49ed-8ab9-52b0c1a0179b&sId=-1)
4) Breugel Working Paper

B) Acknowledgements
Large language models such as ChatGPT have been used to explain the findings better.

Article

Impact of Human Capital Expenditure on Economic Growth in Highly Populated States of India

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Abstract

This study empirically examines the asymmetric short-term and long-term impacts of government expenditure on education and healthcare on economic growth, proxied by Gross State Domestic Product, in the Indian states of Assam, Bihar, MP, Odisha, and UP. Unit root tests confirmed that all variables are integrated at I(0) or I(1). Utilizing Nonlinear Autoregressive Distributed Lag and dynamic multiplier models with annual time series data from 1990 to 2023, the findings reveal statistically significant asymmetric effects of shifts in government education and health expenditure on economic growth in both the short and long run across all states. Additionally, the significant negative coefficients of the Error Correction Terms confirm a long-run equilibrium relationship between economic growth and education and health sector expenditures in every state.

Keywords: Education expenditure, Health expenditure, Economic growth, and NARDL

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Introduction

Human capital is essentially the collective abilities and skill sets of a nation's people. This vital concept was established by pioneering economists like Schultz (1961), Becker (1964), Mincer (1974), and Rosen (1976). Human capital theory uniquely highlights that individual health, alongside education, is crucial for economic growth (Osiobe, 2019). Seminal works in endogenous growth theory, particularly by Mankiw et al. (1992) and Lucas (1988) highlight human capital as a fundamental driver of economic expansion.This theoretical perspective is strongly supported by a vast body of both theoretical and empirical economic literature, which consistently demonstrates the crucial role of human capital in fostering economic growth across nations. Human capital directly enhances individuals' abilities and labour productivity, contributing to economic growth (Bloom & Canning, 2003). Both education and health investments are globally recognized as critical input factors that significantly contribute to national wealth (Manuelli & Seshadri, 2014; Hakooma & Seshamani, 2017; & Leoni, 2025). A nation's economic growth is significantly bolstered by a healthy and educated workforce, as it leads to increased productivity (Yun & Yusoff, 2018). Globally, human capital achievements are regularly employed as key indicators of social and economic advancement (Kotsantonis & George, 2020).

In terms of Human Development Index (HDI), Appendix A reports that most southern and northern states have achieved high HDI scores. Significant development challenges persist in Assam, Bihar, Madhya Pradesh (MP), Odisha, and Uttar Pradesh (UP), which are some of India's most populous states. They have historically lagged behind in economic development, infrastructure, and social services.

The paper is organised as follows: Section II delivers a discusses relevant literature and identifies a research gap. Section III details the econometric models and sources of data. Section IV presents the estimated empirical analysis and findings. Section V presents summary and conclusions.

Review of Literature

Several global studies have highlighted its significant positive influence of investment in education on GDP using time series econometric models. Hussin et al. (2012) in Malaysia showed that government expenditure on education is positively cointegrated with GDP. Mercan & Sezer (2014) in Turkey, and Mekdad et al. (2014) in Algeria found a significant positive association between expenditure on education and economic growth. Mallick et al. (2016) further reinforced this, showing a long-run positive influence of education spending on GDP growth across a panel of Asian countries

Healthcare spending constitutes an essential element of human capital, with direct implications for the workforce's output and overall health. Odior (2011) found a significant positive effect of health expenditure on GDP in Sub-Saharan Africa. Similarly, Babatunde (2014) identified total health expenditures, alongside gross capital formation and labour force productivity, as important determinants of economic growth in Nigeria.

A number of global studies have emphasized the effect of both education and healthcare on economic growth. For instance, Rahman (2011) identified bidirectional causality between education and economic growth in Bangladesh and also unidirectional causality from health expenditure to GDP. In Malaysia, Tang & Lai (2011) found that education expenditure Granger-causes health expenditure in the short-term and long-term, suggesting a societal prioritization of education spending. Maitra & Mukhopadhyay (2012) observed a significant positive influence of education and healthcare expenditure on economic growth across some Pacific and Asian countries, including Bangladesh, Nepal, and Singapore. Similarly, Torruam & Abur (2014) reported bidirectional causality among GDP and human capital development in Nigeria. Adekola (2014) found that federal and state governments' expenditure on specifically education and health has a positive effect on Nigeria's GDP growth, both individually and collectively.

Wong & Yusoff (2015) observed an unidirectional causality from economic growth to education and health outlay in Malaysia. Hakooma & Seshamani (2017) found evidence of a long-run connection among education, health, secondary school enrolment and GDP in Zambia. Sultana et al. (2022), examining a panel of 141 countries, concluded that all aspects of human capital positively influence economic growth in developing countries.

Using the NARDL model, Jiang & Wang (2023) and Oladipo & Peter (2024) found significant asymmetric impact of health and education on GDP in both long and short terms in China and Nigeria, respectively, and a reduction in short-term government health expenditure could lead to a substantial decline in GDP per capita. Alam et al.

(2025) in Saudi Arabia reported a positive association between expenditure on education and economic growth. However, they noted a negative association with healthcare spending.

Within the Indian context, limited earlier studies have examined the connection between education and healthcare expenditures, and GDP. Pradhan (2009), analyzing data from 1951 to 2001, identified a unidirectional causality from GDP to education, suggesting that economic expansion drives increased investment of education in India. This study also noted a short-run dynamic relationship between the two. Subsequently, Sharma & Sahni (2015), examining the period 1991-2013, discovered bidirectional causality among both education and healthcare investments and GDP, indicating more integrated and reciprocal long-run equilibrium relationship for India. Conversely, a more recent study by Mariappan (2019), which focused on Indian states from 1990 to 2017, offered nuanced findings. It reported no cointegration or causal relationship from education and healthcare expenses to GSDP in Gujarat, Jammu and Kashmir, Maharashtra, Punjab, Tamil Nadu, and West Bengal. This underscores the substantial heterogeneity across India and implies that the impact of human capital expenditure may not be uniform across states, possibly due to variations in policy implementation, spending efficiency, or other contextual factors.

In summary, the existing research largely agrees that investing in human capital has a substantial positive effect on economic growth, a view that aligns with established economic theories and is further highlighted by worldwide developments emphasizing human capital's crucial role. Nevertheless, the specific impact and relationships can vary significantly across countries and regions.

A brief review of the available literature suggests that no Indian study has yet employed suitable time series econometric models for a comparative analysis of how education and healthcare spending affect GSDP growth in India's most populous states, specifically Assam, Bihar, MP, Odisha, and UP, using the latest data source covering the period from 1990–1991 to 2022–2023. This study, therefore, addresses a specific research gap in the Indian context.

Objectives of the Study

To bridge this research gap, the current study investigates the long-term and short-term impacts of education and healthcare spending on GSDP in the Indian states previously identified, using the NARDL and Dynamic Multiplier models. These states have recorded lower socio-economic indicators compared to other Indian states. The analysis will provide valuable insights and inform policymakers in India.

Econometric Methodologyand Data

Source of Data

The dataset for this research encompasses government expenditures on education and health, and GSDP, for five Indian states of Assam, Bihar, Madhya Pradesh, Odisha, and Uttar Pradesh over a 33-year period from1990-91 to 2022-23. The required data, comprising PNDP, GSDP, and both revenue expenditure and capital expenditure on education and health were obtained from *State Finances: A Study of Budgets*, RBI spanning various years. The *Handbook of Statistics on Indian States* provides data on HDI, and IMR for Indian states.

Measurement of Variables

This study used real GSDP data for selected states to capture economic growth. The capital and revenue expenditures for education and healthcare are collected and combined by group, and then taken as government Total Expenditure on Education (TEE) and Total Expenditure on Health (TEH). The dependent variable is GSDP (in rupees). The government TEE and TEH (in rupees) are taken as independent variables to capture GSDP.

Human Capital and Economic Growth

Wagner (1883) hypothesized that as a country's per capita income increases, government spending would also rise. The endogenous growth theory supports investment in education and health, as argued by Lucas (1988) and Romer (1990), as it promotes efficiency, knowledge, and innovation, ultimately contributing to economic growth. The growth model proposed by Lucas can be represented as follows:

$$P = AK^{\alpha} (uh)^{1-\alpha} (h_m)^{\psi} \qquad (1)$$

The production function can be represented as follows: Output (P) is a function of physical capital (K), the proportion of time spent on productive activities (u), human capital input (h), and the economy's average human capital (hm). Investments in education and healthcare boost human capital, which then propels output growth through either direct accumulation (uh) or the overall knowledge base (hm). Should $\psi>0$, the production function demonstrates increasing returns to scale, meaning productivity growth is inherent in human capital investments. The Cobb-Douglas Production Function (CDPF) is suitable for modelling this relationship between economic growth and human capital inputs like education and healthcare spending, as follows

$$P_t = AE_t^{\alpha} H_t^{\beta} e_t \qquad \alpha, \beta > 0 \qquad (2)$$

The log-linear CDPF can be written as follow:

$$InP_t = InA + \alpha InE_t + \beta InH_t + Ine_t \qquad (3)$$

where P denotes output of education, A means whole factor productivity, E denotes input of education expenditure, H denotes input of expenditure on healthcare, e denotes the error term and t denotes time period. The parameters α and β represent elasticities of output with respect to government education and healthcare expenditures, respectively. However, the CDPF may not be suitable for examining the short-term and long-term relationships among the time series variables due to the asymmetric effects of changes in education and healthcare outlay on real GSDP. To overcome this limitation, the current study utilizes the Nonlinear Autoregressive Distributed Lag (NARDL) model. This approach is specifically chosen for its ability to uncover both nonlinear relationships and asymmetric effects that education and healthcare expenditures might have on economic growth.

Econometric Models

This study employs multivariate time series econometric models to inspect the expenditure influence of education and health on GSDP in the short- runas well as long-run analyses with help of Eviews software.

Structural Unit Root Test

In the first stage, a unit root by the Zivot-Andrews (1992) was applied to investigate the stationarity of the variables before estimating the NARDL model. Economic time series data often exhibit non-stationarity, and estimating a regression of one non-stationary time series variable on another using Ordinary Least Square (OLS) can lead to spurious regression, resulting in meaningless relationships among variables

(Muftaudeen & Bello, 2014). However, a common issue in time series analysis is the occurrence of structural breaks, which can lead to inconclusive results and affect the degree of stationarity. Economic variables often exhibit asymmetries, making it essential to address these problems. To prevent these issues, this study employs the Zivot-Andrews (ZA) structural break test, which accounts for intercept and trend breaks. The ZA unit root test (Intercept & Trend) is specified as

$$\Delta Yt = \pi + \pi Y_{t-1} + \pi_t + \delta UT_t + \delta DT_t + \sum_{j=1}^{K} dj\Delta Y_{t-j} + \mu t \quad (4)$$

where, UT_t denotes dummy parameter for mean shift arising at each probable break and DTt denotes the trend shift variable.The null hypothesis (H_0) denotes that the data (GSDP, TEE and TEH) are non-stationary. The H_0 can be rejected if the computed ZA statistic exceeds the critical values, indicating that the data are stationary at their levels, and thus, the alternative hypothesis (H_1) is accepted.

NARDL Framework

The NARDL model originally proposed by Pesaran et al. (2001) and later developed by Shin et al. (2014) is a significant development in time series analysis, particularly for examining asymmetric relationships between variables. They argued that nonlinearity is common in economic variables, resulting in asymmetric or non-linear relationships between macroeconomic variables. This technique has been widely used in empirical studies to examine the relationships between variables. Therefore, the present study applies the NARDL model to explore the asymmetric effect of education and on GSDP in the short and longterms. The NARDL technique decomposes variables into two components: (a) the part of positive changes in variables and (b) the part of negative changes in variables. In this study, government TEE and TEH are decomposed into equations (5) and (6) as follows:

$$TEEt = TEE_0 + TEE_t^+ + TEE_t^- \quad (5)$$

$$TEHt = TEH_0 + TEH_t^+ + TEH_t^- \quad (6)$$

In equation (5), TEE_t^+ represents the partial sum of increases in total education expenditure, while TEE_t^- represents the partial sum of decreases in education expenditure. Similarly, in equation (6), TEHt+ represents the partial sum of increases in total health expenditure, and TEH_t^- represents the partial sum of decreases in health expenditure, as shown in equations (7) to (10).

$$TEE_t^{+} = \sum_{i=1}^{t} \Delta TEEi^{+} = \sum_{i=1}^{t} Max(\Delta TEE, 0) \quad (7)$$

$$TEE_t^{-} = \sum_{i=1}^{t} \Delta TEEi^{-} = \sum_{i=1}^{t} Min(\Delta TEE, 0) \quad (8)$$

$$TEH_t^{+} = \sum_{i=1}^{t} \Delta TEHi^{+} = \sum_{i=1}^{t} Max(\Delta TEH, 0) \quad (9)$$

$$TEH_t^{+} = \sum_{i=1}^{t} \Delta TEHi^{+} = \sum_{i=1}^{t} Min(\Delta TEH, 0) \quad (10)$$

where, $\Delta TEE = TEE_t - TEE_{t-1}$ and $\Delta TEH = TEH_t - TEH_{t-1.}$ Within the NARDL model, the short-term and long-term asymmetric dynamics can be incorporated into the following equation:

$$\Delta lnGSDP_t = C + \beta_0 GSDP + \beta_1 ln\, TEE^{+}_{t-1} + \beta_2\, ln\, TEE^{-}_{t-1} + \beta_3\, ln\, TEH^{+}_{t-1} + \beta_4\, ln\, TEH^{-}t\text{-}1 + \sum_{i=1}^{l-1} \lambda_{1i}\, \Delta lnGSDP_{t-1} + \sum_{i=0}^{l-1} [\, \lambda_{2i}\, \Delta lnTEE^{+}_{t-i} + \lambda_{3i}\, \Delta lnTEE^{-}_{t-i}\,] + \sum_{i=0}^{l-1} [\, \lambda_{4i}\, \Delta lnTEH^{+}_{t-i} + \lambda_{5i}\, \Delta lnTEH^{-}_{t-i}] + \varepsilon_t \quad (11)$$

The short term and long term parameters were tested using the following Error Correction Model equation:

$$\Delta lnGSDP_t = C + \sum_{i=1}^{l-1} \lambda_0\, \Delta lnGSDP_{t-i} + \sum_{i=0}^{l-1} \lambda_1\, \Delta lnTEE_{t-i} + \sum_{i=0}^{l-1} \lambda_2 \Delta lnTEH_{t-i} + \theta ECTt + \varepsilon_t \quad (12)$$

Finally, the study uses the NARDL dynamic multiplier model to assess the cumulative effect of changes in explanatory variables on the dependent variable over a period of time. It also employs diagnostic tests to evaluate the overall validity, and Cumulative Sum (CUSUM) and Cumulative Sum of Squares (CUSUMSQ) tests to measure the structural stability of the NARDL model.

Empirical Analysis and Findings

Descriptive Statistics and Correlation

The summary statistics for GSDP, TEE and TEH are reported in Table 2. The estimated results indicate that all variables exhibit positive skewness, with similar means. These findings suggest that the variables are asymmetric. The estimated kurtosis values for all variables are below 3, indicating platykurtic distributions across all states. Total Education Expenditure (TEE) in Odisha displays high variability based on the standard deviation results, much more so than other variables. This pronounced variability is also indicative of data asymmetry. It implies that asymmetric econometric techniques are suitable for examining the relationship between GSDP, and TEE and TEH.

The study also applied Pearson Correlation to understand the relationships among the variables used. The estimated results showed that the GSDP expected a significant positive correlation with government TEE and TEH in all the states. This finding is confirmed with the theoretical prediction, where a rise in human capital improves the economic growth of a nation. The estimated results of the Zivot-Andrews (ZA) structural break unit root test are presented in Table 3.

Table 2: Estimated Results of Descriptive Statistics

State	Observation	Mean	Standard. Deviations	Minimum Value	Maximum Value	Skewness	Kurtosis	Variable	Pearson Correlation		
									GSDP	*TEE*	TEH
Assam	33	15.725	1.138	13.876	17.714	0.118	-1.087	GSDP	1.000		
	33	12.307	1.130	10.726	14.746	0.922	-0.040	TEE	0.713	1.000	
	33	10.884	1.382	9.459	13.884	1.246	0.349	TEH	0.709	0.982	1.000
Bihar	33	16.245	1.144	14.640	18.135	0.193	-1.378	GSDP	1.000		
	33	12.966	1.087	11.583	15.522	1.123	0.403	TEE	0.678	1.000	
	33	11.965	1.272	10.343	14.717	0.954	-0.219	TEH	0.875	0.810	1.000
MP	33	16.669	1.175	14.930	18.700	0.210	-1.268	GSDP	1.000		
	33	12.736	1.077	11.476	15.140	1.241	0.534	TEE	0.719	1.000	
	33	11.653	1.227	10.246	14.643	1.479	1.244	TEH	0.747	0.989	1.000
Odisha	33	16.136	1.279	13.902	18.166	0.060	-1.283	GSDP	1.000		
	33	12.196	0.990	10.741	14.778	0.912	0.471	TEE	0.655	1.000	
	33	11.178	1.360	9.551	14.642	1.288	0.962	TEH	0.766	0.912	1.000
UP	33	17.379	1.107	15.529	19.235	0.090	-1.153	GSDP	1.000		
	33	13.602	1.029	12.234	15.694	0.896	-0.129	TEE	0.758	1.000	
	33	12.599	1.204	11.121	15.593	1.141	0.494	TEH	0.825	0.971	1.000

Source: Author’s estimation

Table 3: Estimated Results of Zivot-Andrews Unit Root Test with Trend and Constant

State	Critical Values @1% = -5.34, 5 % = - 4.80, 10% = - 4.58				
	Variable	t-Statistic	At Level/ First Probability Value	difference Break point	Order of Integration
Assam	GSDP	-9.9364	0 .0001	2016	I(0)
	TEE	-7.5739	0.0001	2011	I(0)
	TEH	-5.2376	0.0601	2015	I(1)

Bihar	GSDP	-5.6249	0.0003	2016	I(0)
	TEE	-6.6966	0.0000	2011	I(0)
	TEH	-6.1004	0.0491	2005	I(1)
MP	GSDP	-6.9914	0.0342	2008	I(1)
	TEE	-4.0941	0.0010	2011	I(0)
	TEH	-6.0501	0.0000	2011	I(0)
Odisha	GSDP	-8.2648	0.0068	2003	I(1)
	TEE	-6.3964	0.0000	2011	I(0)
	TEH	-8.7501	0.0000	2011	I(0)
UP	GSDP	-8.6408	0.0007	2016	I(0)
	TEE	-6.9668	0.0000	2011	I(0)
	TEH	-7.1070	0.0586	2010	I(1)

Source: Author's estimation

The variables in this study exhibit a mixed order of integration, meaning some are stationary at their level (I(0)) while others become stationary after one differencing (I(1)). Importantly, none of the variables are integrated of order I(2)**.** This specific characteristic of the data makes the NARDL Nonlinear Autoregressive Distributed Lag model an ideal choice for investigating their cointegration relationship. Additionally, the results reveal that a structural break occurred between 2000 and 2017.

Results of NARDL Bound Test

Next, the present study applied the NARDL bounds test to examine the short-term and long-term influence of TEE and TEH on GSDP. The estimated results of bounds test are reported in Table 4. The findings indicate that the calculated F-statistics for all five states exceed the upper I(1) bound values in significance at 1, 5 or 10 per cent levels, suggesting that the variables used are cointegrated at I(0) and I(1).

Table 4: Estimated NARDL Bound Test

Null Hypothesis: No levels relationship						
State	F-statistics	K	Critical Value	Lower bound I(0)	Lower bound I(1)	Decisions (Outcome)
Assam	54.15309	4	10 %	2.2	3.09	Cointegration
Bihar	8.467978	4	5 %	2.56	3.49	Cointegration
MP	4.861657	4	2.5 %	2.88	3.87	Cointegration
Odisha	5.661887	4	1 %	3.29	4.37	Cointegration
UP	12.97204	4				Cointegration

Source: Author's estimation

Results of NARDL

The estimated results of the NARDL model, presented in Tables 5 to 7, reveal that changes in government TEE and TEH have statistically significant and asymmetric effects on GSDP in both the short-term and long-term analyses.

Table 5: Estimates of NARDL Model by State

Dependent Variable = GSDP						
	Assam			Bihar		
	Short-Term Coefficients			Short-Term Coefficients		
Variable	Coefficient	t-Statistic	Prob.	Coefficient	t-Statistic	Prob.
D(GSDP(-1))	-1.398176	-26.16049	0.0000	0.659833	2.530600	0.0190
D(GSDP(-2))	2.897458	19.53657	0.0000	0.225993	1.140039	0.2665
D(GSDP(-3))	-2.897458	-11.23485	0.0001	0.130261	0.668602	0.5107
D(TEE_POS)	3.817816	23.49799	0.0000	2.312010	5.541981	0.0001
D(TEE_POS(-1))	3.406976	14.58626	0.0000	-0.337503	-0.58726	0.5679
D(TEE_POS(-2))	7.720365	24.05224	0.0000	1.909011	3.456251	0.0047
D(TEE_POS(-3))	0.791483	20.26069	0.0000	0.149562	1.283267	0.2236
D(TEE_NEG)	0.429836	0.966369	0.3782	-0.101618	-2.287155	0.0411

D(TEE_NEG(-1))	-12.74536	-17.90763	0.0000	-0.519498	-4.835870	0.0004
D(TEE_NEG(-2))	-12.06534	-19.47971	0.0000	-0.579450	-6.020284	0.0001
D(TEE_NEG(-3))	-2.654230	-6.099927	0.0017	-0.429889	-7.940481	0.0000
D(TEH_POS)	0.111312	1.374207	0.0278	-1.688950	-5.377735	0.0002
D(TEH_POS(-1))	-3.588247	-18.62075	0.0000	0.458414	0.931183	0.3701
D(TEH_POS(-2))	-6.746411	-23.55386	0.0000	-1.700651	-3.446640	0.0048
D(TEH_POS(-3))	6.746411	6.051221	0.0018	0.202448	0.409140	0.6911
D(TEH_NEG)	0.302657	0.681571	0.5258	-0.327769	-4.095230	0.0015
D(TEH_NEG(-1))	14.08452	18.62436	0.0000	-0.277021	-2.170594	0.0507
D(TEH_NEG(-2))	11.82389	19.25780	0.0000	0.223861	0.688602	0.5067
D(TEH_NEG(-3))	2.547289	5.824580	0.0021	-0.072105	-0.267551	0.7945
ECT	-0.644887	-25.49190	0.0000	-0.721005	-8.483974	0.0000
	Long-Term Coefficients			Long-Term Coefficients		
TEE_POS	2.426431	2.124394	0.0870	4.216608	11.36859	0.0000
TEE_NEG	-17.45367	-3.474305	0.0178	-0.142002	-6.766985	0.0000
TEH_POS	2.209582	2.353009	0.0653	-3.182596	-8.909433	0.0000
TEH_NEG	-16.77111	3.555748	0.0163	-0.117970	-0.532543	0.6041
Constant	13.51843	55.80333	0.0000	15.18956	149.3757	0.0000
R-squared		0.793446			0739305	
Adjusted R-squared		0.782305		0.71056		
Observation		33		33		

Source: Author's estimation

The NARDL results revealed that the effect of TEE and TEH on GSDP is not uniform and exhibit asymmetries across states. The short term results indicated that a 1 per cent increase in TEE leads to significant increases in GSDP across states, with estimated increase of 3.81 per cent in Assam, 2.31 per cent in Bihar, 0.33 per cent in MP, 0.08 per cent in Odisha and 0.24 per cent in UP .

This finding is consistent with former studies of Adekola (2014) Mercan & Sezer

(2014), Maitra & Mukhopadhyay (2012), and Oladipo & Peter (2024). Further analysis reveals that all positive shocks to TEE (lagged periods) are significantly and positively correlated with GSDP in Assam, MP, and UP, but not in Odisha. All the negative shocks to TEE (lagged periods) are significantly and negatively correlated with GSDP in Assam and Bihar, but in MP. The results suggest that a 1unit or 1 per cent rise in TEH has varying effects on the GSDP of different states in the short term. Specifically, a 1 per cent rise in TEH leads to a 0.11, 0.16 and 0.76 per cent increase in GSDP of Assam, Odisha, and UP, respectively. In contrast, a 1 per cent increase in TEH results in a 1.68 and 0.05 per cent fall in GSDP of Bihar and MP, respectively.

A negative variation in TEH leads to a decay in GSDP, suggesting that reduced government investment in healthcare results in poor health status and ultimately affects economic growth. The results explore the association between TEH shocks and GSDP in lagged periods, finding that positive shocks of TEE are negatively associated with GSDP in Assam, MP, and Odisha, but positively correlated in Bihar. Conversely, negative shocks of TEH are positively associated with GSDP in Assam and UP, but negatively correlated in MP in short terms. These findings align with previous research by Adekola (2014), Maitra & Mukhopadhyay (2012), and Jiang & Wang (2023).

The estimated coefficients of ECT are exhibit appropriate signs confirming a long-term relationship between the GSDP, TEE and TEH across all states. The ECT coefficients indicate that approximately 64.5, 72.1, 12.6, 13.7, and 11.9 percentages of short-run deviations from the long-run equilibrium are corrected each period in Assam, Bihar, MP, Odisha, and UP, respectively.

Table 6: EstimatedResults of NARDL Model by State

Dependent Variable = GSDP						
	MP			Odisha		
	Short-Term	Coefficients	Short-Term		Coefficients	
Variable	Coefficient	t-Statistic	Prob.	Coefficient	t-Statistic	Prob.
D(GSDP(-1))	-1.027717	-4.498699	0.0064	-0.541618	-3.321325	0.0077
D(GSDP(-2))	-0.491785	-2.886774	0.0343	-0.395875	-2.424605	0.0358
D(GSDP(-3))	0.491785	1.776222	0.1359	-0.434517	-2.763457	0.0200
D(TEE_POS)	0.334622	4.051515	0.0098	0.084047	1.316311	0.2174

D(TEE_POS(-1))	0.109149	1.521440	0.0886	-0.205828	-4.158784	0.0020
D(TEE_POS(-2))	0.221209	2.182444	0.0809	-0.095691	-1.897980	0.0869
D(TEE_POS(-3))	-0.221209	-0.790454	0.4651	-0.345263	-4.556232	0.0010
D(TEE_NEG)	-0.192826	-2.069804	0.0933	0.230679	2.840780	0.0175
D(TEE_NEG(-1))	1.851972	6.977842	0.0009	-0.122786	-2.020295	0.0709
D(TEE_NEG(-2))	2.583791	6.354354	0.0014	-0.110551	-2.120656	0.0600
D(TEE_NEG(-3))	1.021291	2.653400	0.0452	-0.249572	-1.638685	0.1323
D(TEH_POS)	-0.058540	-0.641799	0.5493	0.160599	3.159947	0.0102
D(TEH_POS(-1))	0.231128	3.259303	0.0225	-0.205828	-2.050021	0.0675
D(TEH_POS(-2))	-0.223231	-2.274016	0.0721	-0.095691	-1.101844	0.2963
D(TEH_POS(-3))	-0.109845	-2.755312	0.0401	-0.345263	-2.893400	0.0160
D(TEH_NEG)	0.191313	1.771596	0.1367	-0.219516	-2.613182	0.0259
D(TEH_NEG(-1))	-2.267736	-7.303321	0.0008	-0.122786	-3.872693	0.0031
D(TEH_NEG(-2))	-3.149813	-6.404187	0.0014	-0.110551	-3.640504	0.0045
D(TEH_NEG(-3))	-1.291170	-2.777006	0.0390	0.110551	2.120656	0.0600
ECT	-0.126851	-6.807340	0.0010	-0.137003	-7.138416	0.0000
		Long-Term Coefficients			Long-Term Coefficients	
TEE_POS	3.616840	1.299455	0.2505	-2.146919	-1.326028	0.2143
TEE_NEG	-4.194198	-0.782610	0.4693	-3.017384	-2.312578	0.0433
TEH_POS	-2.913180	-0.939354	0.3907	3.140535	1.832977	0.0967
TEH_NEG	5.524567	0.883239	0.4175	-1.358178	-1.631089	0.1339
Constant	16.86806	16.02687	0.0000	17.15297	11.37414	0.0000
R-squared		0.918916			0.735710	
Adjusted R-squared		0.781074			0.524279	
Observation		33			33	

Source: Author's estimation

The estimated results reveal asymmetric influences of TEE and TEH on GSDP in the long term. A 1per cent positive change in TEE leads to significant increases in GSDP in Assam (2.42 per cent), Bihar (4.21 per cent), MP (3.61 per cent), and UP (5.05 per cent), but decreases in Odisha (-2.14 per cent). Conversely, a 1 per cent negative change in TEE results in decrease in GSDP in Assam (17.45 per cent), Bihar (0.14 per cent), Odisha (3.01 per cent) and MP (-4.19 per cent), but an increase in UP (7.05 per cent).

Table 7: Estimate Results of NARDL Model by State

Dependent Variable = GSDP							
Short-Term Coefficients				Long-Term Coefficients			
Variable	Coefficient	t-Statistic	Prob.	Variable	Coefficient	t-Statistic	Prob.
D(GSDP(-1))	-1.259922	-8.404306	0.0035	TEE_POS	5.059707	3.632315	0.0359
D(GSDP(-2))	2.375982	9.197098	0.0027	TEE_NEG	7.057918	4.705212	0.0182
D(GSDP(-3))	2.597773	8.455957	0.0035	TEH_POS	2.683398	3.508764	0.0392
D(TEE_POS)	0.243339	1.147623	0.0343	TEH_NEG	-1.90676	-5.007492	0.0153
D(TEE_POS(-1))	1.995924	5.676610	0.0108	Constant	1.020628	0.224021	0.8371
D(TEE_POS(-2))	2.278502	7.636093	0.0047				
D(TEE_POS(-3))	2.294292	8.669540	0.0032				
D(TEE_NEG)	2.954068	12.12173	0.0012				
D(TEE_NEG(-1))	0.561811	1.823784	0.1657				
D(TEE_NEG(-2))	-0.457861	-1.234034	0.0350				
D(TEE_NEG(-3))	-1.517556	-4.712234	0.0181				
D(TEH_POS)	0.766105	5.189627	0.0139				
D(TEH_POS(-1))	-1.176960	-5.170663	0.0140				
D(TEH_POS(-2))	-2.482004	-9.399524	0.0026				
D(TEH_POS(-3))	-1.453828	-6.347835	0.0079				
D(TEH_NEG)	-3.610989	-9.239173	0.0027				
D(TEH_NEG(-1))	-0.222806	-0.382557	0.7275				
D(TEH_NEG(-2))	0.424057	0.624798	0.5764				
D(TEH_NEG(-3))	2.824550	4.753676	0.0177				
ECT*	0.119865	14.40669	0.0007				
R-squared		0.988494					
Adjusted R-squared		0.761168					
Observation		33					

Source: Author’s estimation

A 1 per cent positive change in TEH leads to increases in GSDP in Assam (2.20 per cent), Odisha (3.14 per cent), and UP (2.68 per cent), but decreases in Bihar (3.18 per cent) and MP (-2.91 per cent). Similarly, a 1 per cent negative change in TEH results in an increase in GSDP in MP (5.52 per cent), but decreases in Assam (-16.77 per cent), Bihar (-0.11 per cent), Odisha (-1.35 per cent), UP (-1.90 per cent). The adjusted R^2 values indicate that TEE and TEH jointly explain GSDP by 78 per cent in Assam, 71 per cent in Bihar, 78 per cent in MP, 52 per cent in Odisha, and 76 per cent in UP. A low adjusted R^2 value is recorded in Odisha.

NARDL Dynamic Multiplier

The estimated results of the NARDL dynamic multiplier across the states are reported in Figure 1. In all Figures from 1 A to 1 J of dynamic multipliers, the time period and monetary unit are measured on the horizontal axis and vertical axis, respectively. In case of Assam, Bihar, Odisha, and UP, the visual representation differentiates positive TEE shifts with aprominent solid top line and negative shifts with a bold dashed bottom line**.** A central thick dotted red line explicitly tracks the asymmetric impact, reflecting the varied multiplier effects of positive and negative expenditure shocks on GSDP through the years. The thin dotted reds lines above and below, without specific labels, denote the 95 per cent confidence level, establishing the statistical relevance of this asymmetry. Crucially, if the zero line is encompassed by these confidence boundaries, the asymmetry lacks statistical significance at the 5 per cent thres hold.

Figures 1 A to 1 E reveal that a positive shock of TEE has a greater effect on economic performance (GSDP) compared to a negative shock of TEE throughout the period in Assam, MP, and UP states until the period's end. This finding is similar to Alam et al. (2025). A similar effect is observed from the NARDL model in these states.

Figure 1: Estimated Results of NARDL Dynamic Multiplier

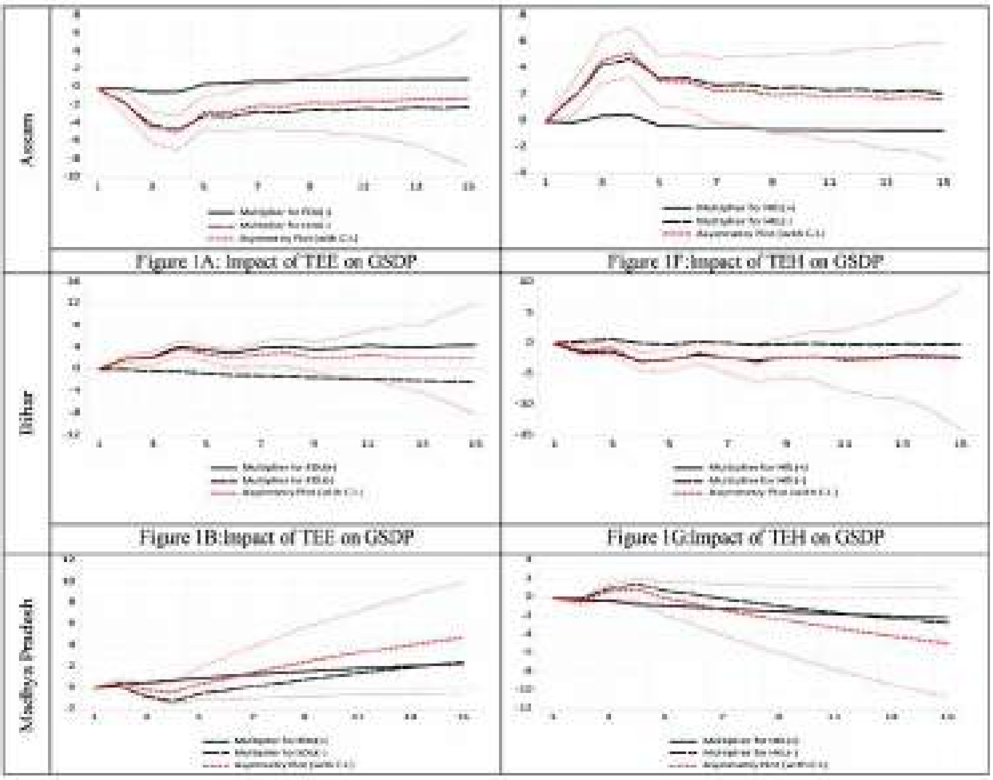

Figure 1A: Impact of TEE on GSDP

Figure 1F: Impact of TEH on GSDP

Figure 1B: Impact of TEE on GSDP

Figure 1G: Impact of TEH on GSDP

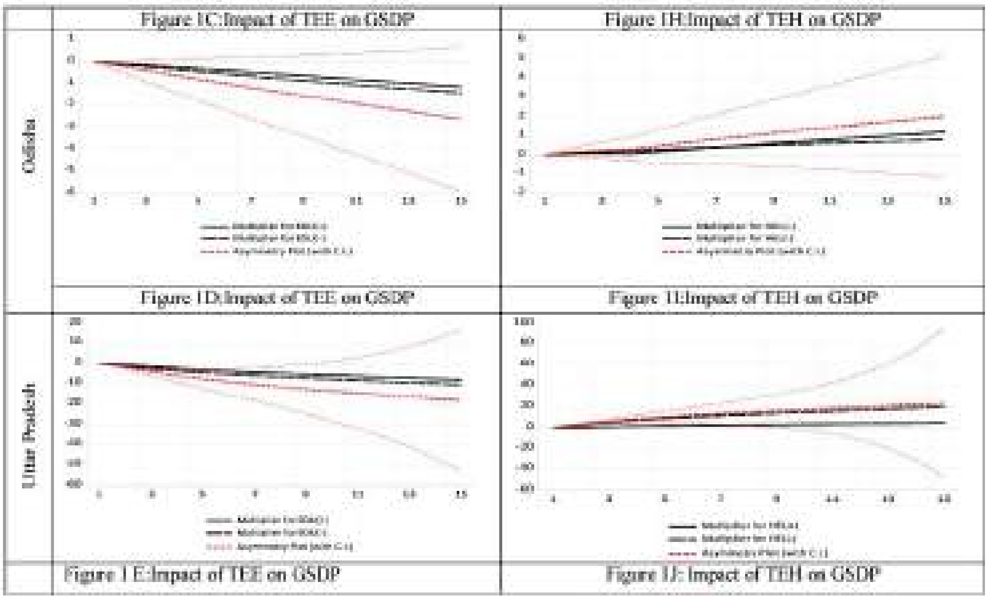

Figure 1C: Impact of TEE on GSDP

Figure 1H: Impact of TEH on GSDP

Figure 1D: Impact of TEE on GSDP

Figure 1I: Impact of TEH on GSDP

Figure 1 E: Impact of TEE on GSDP

Figure 1J: Impact of TEH on GSDP

Source: Author’s estimation

Similarly, Figures from 1 F to 1 J indicate that stronger negative than positive TEH shock impacts GSDP throughout the period, lying above zero in Assam and UP states only until the period's end. This finding is similar to Alam et al. (2025). The negative impact of TEH in MP demonstrates an interesting trajectory: it is initially positive, but then reverses tonegative from the sixth year, continuing that trend for the remainder of the period. This agrees with the findings of Jiang & Wang (2023).

In Odisha, positive shocks of TEE have a positive wave on GSDP throughout the period. The estimated results of dynamic multiplier show that the impact of positive shocks of TEE expenditure on GSDP is highly significant than the impression of negative shocks of TEE expenditure in in Assam, Bihar, MP and UP. In Assam, Bihar, MP, and UP, the dynamic multiplier results clearly show that positive shocks of TEE have a more substantial effect on GSDP than negative shocks of TEE**.**

Results of Diagnostic and StabilityTests

The computed results of various diagnostic tests are reported in Table 8. The diagnostic tests help to verify assumptions such as normality of residuals, absence of serial correlation, homoskedasticity, and model specification, providing a comprehensive evaluation of the model's performance. The study employs the structural stability tests. The null hypothesis (H_0) posits that there is no structural change in parameters, while the alternative hypothesis (H_a) suggests that a structural change exists. The results, presented in Figure 2 (state-wise), indicate that both Cusum and Cusum-square tests lines fall inside the critical bounds at a 5 per cent level of significance. Consequently, the H_0 cannot be rejected, implying that the NARDL is structurally stable for estimating shortand long runs coefficients during the study period.

Table 8: Estimated Results of NARDL Diagnostic Tests

Diagnostic Tests Statistic (Chi-Square Probability Value)		Probability Value			Decision
Assam	Test (1)	JBS3.4910.174			Rejected Null hypothesis
	Test (2)	FS	1.7460.	314	Rejected Null hypothesis
		OBRS	15.063	(0.005)	
	Test (3)	FS	4.875	0.036	Not Rejected Null hypothesis
		OBRS	4.406	(0.035)	
	Test (4)	TS	1.329	0.254	Not Rejected Null hypothesis
		FS	1.767	0.254	

Bihar	Test (1)	JBSO.8680.647			Rejected Null hypothesis
	Test (2)	FS	1.955	0.192	Rejected Null hypothesis
		OBRS	7.871	(0.019)	
	Test (3)	FS	2.603	0.119	
		OBRS	2.546	(0.110)	Not Rejected Null hypothesis
	Test (4)	TS	3.929	0.002	
		FS	15.444	0.002	Rejected Null hypothesis
MP	Test (1)	JBS3.5920.165			Rejected Null hypothesis
	Test (2)	FS	23.475	0.014	
		OBRS	26.318	(0.000)	Rejected Null hypothesis
	Test (3)	FS	1.623	0.214	
		OBRS	1.646	(0.199)	Not Rejected Null hypothesis
	Test (4)	TS	0.344	0.747	
		FS	0.118	0.747	Rejected Null hypothesis
Odisha	Test (1)	JBS1.2220.542			Rejected Null hypothesis
	Test (2)	FS	5.507	0.031	
		OBRS	16.219	(0.000)	Rejected Null hypothesis
	Test (3)	FS	1.785	0.193	
		OBRS	1.800	(0.179)	Not Rejected Null hypothesis
	Test (4)	TS	0.125	0.902	
		FS	0.015	0.902	Not Rejected Null hypothesis
UP	Test (1)	JBS	2.510	0.284	Rejected Null hypothesis
	Test (2)	FS	4.435	0.318	
		OBRS	25.162	(0.000)	Rejected Null hypothesis
	Test (3)	FS	5.654	0.025	
		OBRS	4.980	(0.025)	Not Rejected Null hypothesis
	Test (4)	TS	2.076	0.173	
		FS	4.313	0.173	Not Rejected Null hypothesis

Null hypothesis (H_0)of Diagnostic Tests

Test (1) - Jarque-Bera (JB)- Normality : Residualare Normally Distributed

Test (2) -Breusch-Godfrey LM : Residuals are not serially correlated

Test (3) -Heteroskedasticity (ARCH)Test : Residuals are not Heteroskedasticity

Test (4) -Ramsey RESET Test : NARDL model is properly specified

Note: JBS = Jarque-Bera Statistic,TS= T-statistic, FS = F-statistic, OBRS= Obs* R-Squared

Source: Author’s estimation

Figure 2:Results of Cusum andCusumSquare Tests

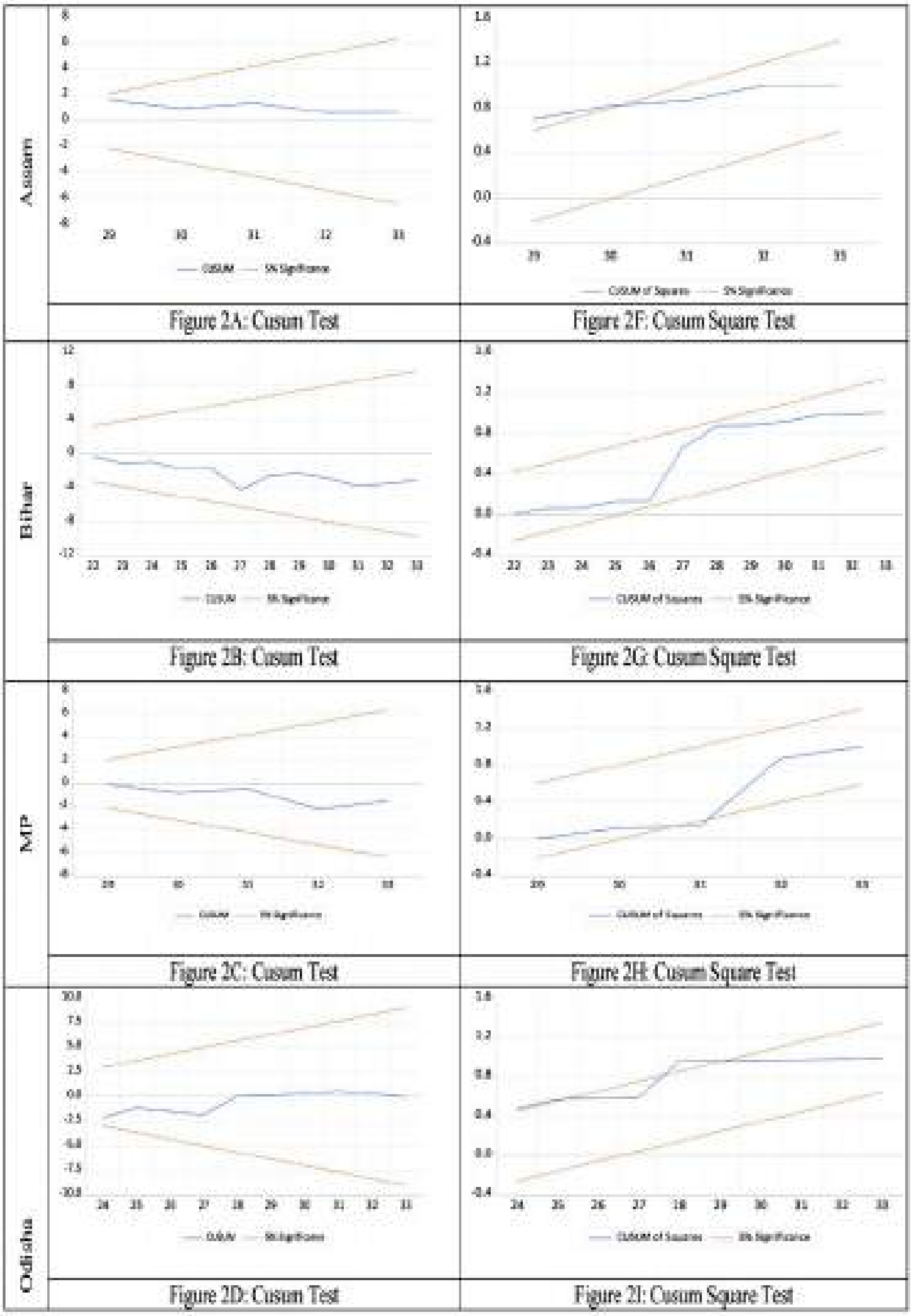

Figure 2A: Cusum Test

Figure 2F: Cusum Square Test

Figure 2B: Cusum Test

Figure 2G: Cusum Square Test

Figure 2C: Cusum Test

Figure 2H: Cusum Square Test

Figure 2D: Cusum Test

Figure 2I: Cusum Square Test

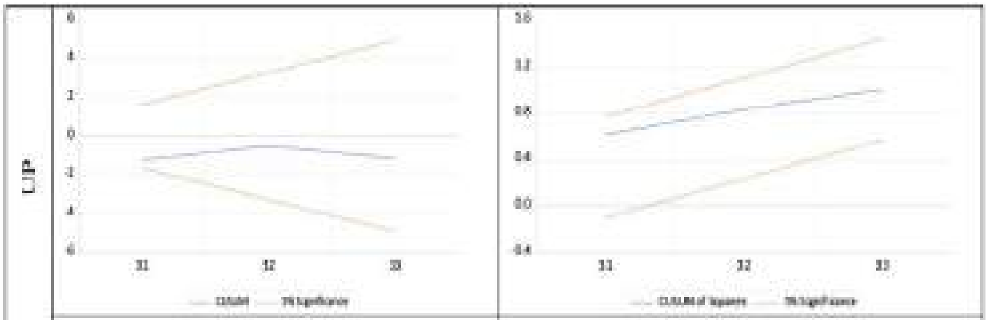

Figure 2E: Cusum Test

Figure 2J: Cusum Square Test

Source: Author's estimation

Concluding Observations

This study examines the asymmetric relationship between education and healthcare expenditure and economic growth (GSDP) in high-population Indian states. The key findings reveal a high positive association among total education and health expenditures and GSDP. GSDP, TEE, and TEH show a mixed order of integration, meaning some are stationary at their initial level (I(0)) while others require one differencing to become stationary (I(1)). Regardless, the NARDL model confirms a long-run equilibrium relationship exists between TEE, TEH, and GSDP across all the states studied, as indicated by the error correction terms (ECT) with expected signs. Furthermore, the results show that positive shocks to TEH lead to increases in GSDP in Assam, Odisha, and UP, but decreases in Bihar and MP. The estimated results of the NARDL dynamic multiplier indicate that GSDP responds more significantly to positive TEE shocks than to negative TEE shocks during the study period in Assam, Bihar, and MP states. These findings provide valuable insights into the complex relationships between education and healthcare and highly populated states of economic growth.

The study's findings have significant policy implications, highlighting the need for increased investments in education and healthcare to achieve better outcomes and promote economic growth. Although the NARDL regression results show that TEE and TEH have positive coefficients, their effects on GSDP are relatively low in short and longterms analyses. Notably, the estimated adjusted R^2 value indicates that TEE and TEH jointly explain only about 52 per cent of the variation in GSDP in Odisha. To address this, both central and state governments should prioritize enlarged expenditures in education and healthcare, which can contribute to states' economic growth and help reduce gender and economic inequalities across Indian states.

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Appendix A: Performance of Socio-Economic Indicators in HighlyPopulated States

Major Populated States of India	Population 2011 (Rank)	Rank of Per capita Net Domestic Product (PNDP)					Rank of HDI					IMR	Rank
		2005	2010	2015	2020	2022	2005	2010	2015	2020	2022	2019-2021	
UP	01	16	11	32	32	32	33	35	35	34	35	50	1
Maharashtra	02	26	31	10	14	13	15	16	16	13	12	36	4
Bihar	03	33	33	33	33	33	36	36	36	36	36	47	2
WB	04	NA	NA	NA	23	23	27	28	28	28	27	22	14
AP	05	18	18	19	18	18	31	27	27	26	25	30	8
MP	06	07	07	28	25	25	34	33	33	33	34	41	3
TN	07	17	15	11	08	25	16	15	14	15	14	19	13
Rajasthan	08	15	04	21	22	21	32	32	29	25	23	30	8
Karnataka	09	09	12	08	07	06	24	26	22	19	18	25	11
Gujarat	10	08	10	13	10	10	23	25	23	24	24	31	7
Odisha	04	05	05	27	26	22	35	34	32	31	33	36	4
Kerala	12	31	30	07	12	11	07	04	01	01	01	04	16
Jharkhand	13	14	16	31	31	31	21	29	34	35	31	27	15
Assam	14	19	29	29	29	29	30	31	30	32	32	33	5
Punjab	15	25	23	16	19	19	14	13	09	11	10	28	9

Source: UNDP reports, Indian National Development Reports and RBI Reports
Notes:(i). Very High (or) High HDI = from 0.700 to 0.899
(ii). Medium HDI = 0.500 to 0.699
(iii). Low HDI = from d" 0.250 to 0.499.

Research Note / Commentary / Perspectives

Labour Migration from Western Odisha and Employment Potential of MSMEs: A Panel Data Analysis

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Abstract

The vagaries of nature, crop failure, lack of irrigation facilities, marketing and storage problems, and undeveloped agro-based industries are some of the reasons behind loss of interest in farming among the rural mass resulting in large scale migration to other states. The present study, using secondary data, attempts to explore the employment potential of the Micro, Small and Medium Enterprises (MSMEs) sector throughout western Odisha, a region experiencing significant interstate migration. The panel data analysis suggests that with an increase in setting up MSMEs in the region employment opportunities will be opened up and the migration can be prevented.

Keywords: Employment, MSMEs, Labour migration, Western Odisha

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1. Introduction

The state of Odisha, basically an agrarian economy, is witnessing a rapid structural transformation with declining share of agricultural sector to GSDP (26%), while that of industrial sector and services sector being 32 per cent and 41 per cent, respectively. With more than 70 per cent of the population relying on agriculture for their livelihood the per capita income in the farming sector is very poor. In addition to this the state faces series of natural calamities which tell upon the productivity in agricultural sector making it an uncertain source of income. Low productivity, crop failure, lack of irrigation facilities, storage and marketing problems are some important reasons for agriculture not being a lucrative occupation. Attraction towards white collar job and urban lifestyle and expectation of better livelihood opportunities among the young mass adds to the problem. As a result, huge movement of labour forces from rural to urban and from farm activities to non-farm activities is seen in recent past. Farmers have lost interest in farming and migrating to other states as bonded labour. The incidence of migration is more in western Odisha. Furthermore, the main cause of migration in western Odisha is the lack of local job possibilities, which pushes many people-especially those from indigenous and underprivileged communities-to look for work away from home.

The existence of socio-political difficulties—such as ineffective governance, inadequate policy implementation, and social marginalization—along with underdevelopment, characterized by poor infrastructure, limited industrial growth, and lack of basic amenities, and widespread poverty, fuels distress migration as a means of survival (Bhattamishra, 2020). In this context, the MSME sector emerges as a vital driver of income generation and employment, with the potential to curb rural labour migration by creating local job opportunities. Recognized as a major contributor to economic growth and equitable development, MSMEs significantly enhance employment across diverse sectors and regions (Anuj et al., 2023). By leveraging local resources and skills, they promote regional development (Pradhan & Munda, 2010). Therefore, fostering the growth of MSMEs in western Odisha could address unemployment effectively while mitigating the socio-economic challenges associated with distress-driven outmigration.

The objectives of the study are

1. To explore the reasons of migration in western Odisha

2. To study the employment potential of MSMEs in the districts of western Odisha

1. Data Sources and Methodology

1.1 Data Description

The study analyses secondary data collected from sources such as annual reports of MSMEs (Government of India), Districts Industrial Profile (https://dcmsme.gov.in/dips/Orissa_dipr.html), and *Economic Survey* of Government of Odisha from 1999-2000 to 2018-2019. We use panel data of migration prone districts of western Odisha such as Balangir, Nuapada, Kalahandi, Sonepur, Sambalpur, Bargarh, Boudh and Kandhamal. This paper estimates the effectiveness of investment and number of MSMEs on employment generation in these districts. Employment has been taken as a dependent variable whereas MSME units and investment as independent variables. All the variable are converted into natural logarithm form to simplify the analysis.

1.2 Model Specification

(a) Pooled Ordinary Least Square (POLS)

The equation for panel data (Brooks, 2014) can be stated as;

$$Y_{it} = \alpha + \beta x_{it} + u_{it} \quad (1)$$

where Y_{it} is dependent variable (Employment)

α = the intercept

β = k ×1 vector of parameters which is determined on the explanatory variables.

x_{it} = 1 × k vector observations on the explanatory variables

i = 1, 2, ……, N (Number of cross sections)

t = 1, 2,……., T (Number of time periods)

(b) Random Effect Model (REM)

$$Y_{it} = \alpha + \beta x_{it} + u_i + \varepsilon_{it} \quad (2)$$

where

i = 1,2, ..., N and t = 1,2, ..., T.

N = number of cross sections

T = the number of time periods.

ε_{it} = the residual as a whole where the residual is a combination of Cross section and time series.

u_i = the individual residual which is the random characteristic of ith unit observation

In first stage we use fixed effect model and random effect regression model to study the linkages between employment, investment and number of units in MSME sector. And next to investigate the presence of long run relationship between unit, investment and employment of MSME, panel cointegration methods is employed. And then to study the impact of MSMEs and investment on employment generation in MSMEs, we apply cointegrating regression model such as Fully Modified Ordinary Least Square (FMOLS) of Phillips and Moon (1999) and Dynamic Ordinary Least Square (DOLS) of Kao and Chiang (2000). In order to apply FMOLS and DOLS technique first stationarity properties of the variables are examined through Levin, Lin & Chu test and Im, Pesaran and Shin W-stat test.

2. Result & Discussion

2.1 Labour Migration in Western Odisha

Western Odisha has long grappled with significant poverty and underdevelopment, particularly in the Kalahandi-Balangir-Koraput (KBK) region, which has been a primary source of distress migration. Persistent challenges such as chronic poverty, recurrent droughts, and limited employment opportunities have compelled many residents to migrate to other states in search of work (Wikipedia contributors, 2025). Mishra, 2024 highlights that seasonal migrants from western Odisha predominantly come from households that are poor, socially disadvantaged, less educated, indebted, and landless. These individuals often engage in low-paying, informal sector jobs under precarious conditions. The incidence of seasonal migrants belonging to the Scheduled Castes (SCs) and Scheduled Tribes (STs) is more from the western region in comparison to the coastal region (Figure 1). It is also recorded that female labour migration rate is much higher in western Odisha than that in coastal area (Figure 2).

Figure 1: Seasonal Migration in Odisha

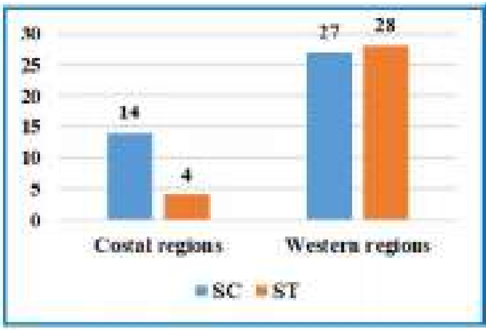
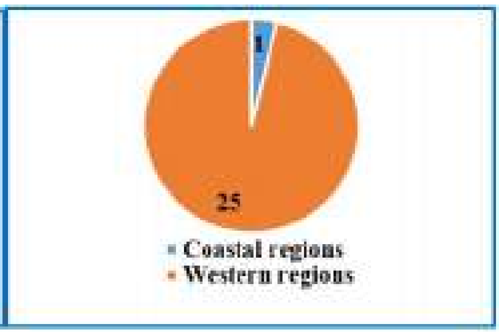


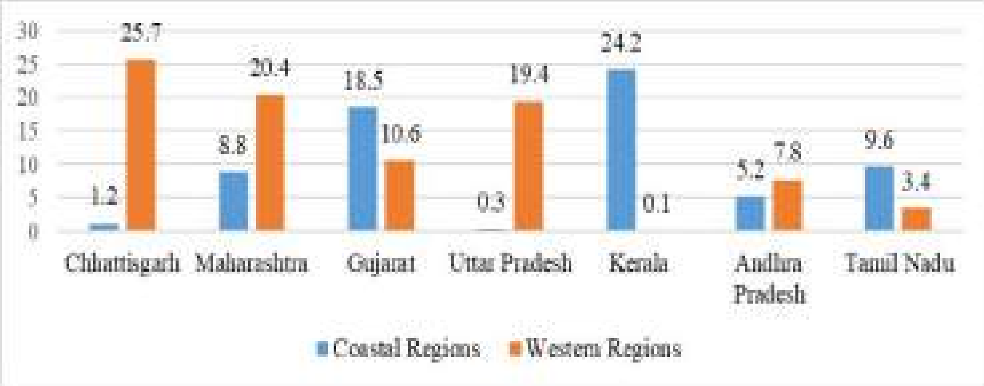
Figure 2: Seasonal Female Migration



Source: Panchayat Census Data, 2010 – 2013

Widespread illiteracy compels migrants to seek mostly manual and unskilled work. Near about 40 per cent of the migrants in both coastal and western regions are either illiterate or can hardly sign their names. About, 66 per cent of workers from the coastal region and 88 per cent from western region of Odisha migrate to other states to get work.

Figure 3: Seasonal Migration from Coastal and Western Odisha to Major States



Source: Panchayat Census Data, 2010 – 2013

Majority of migrant workers are engaged in the construction sector, brick kilns, and agriculture and transportation activities in the destination states as (Figure 3). It is proposed that development of MSMEs in western districts can absorb the growing labour force and can reduce the magnitude of migration. This study examines the employment potential of MSMEs in western Odisha.

2.2 Harnessing MSMEs for Economic Growth and Migration Reduction in Western Odisha

Migration in Western Odisha is often driven by limited employment opportunities, compelling people to seek livelihoods elsewhere. However, the region is endowed with rich natural resources, skilled artisans, and a strong agricultural base. By promoting MSMEs tailored to local strengths, sustainable economic growth can be achieved while curbing migration. Several key sectors hold immense potential for MSMEs in western Odisha:

Agro-Processing, Food and Dairy: Western Odisha's fertile land supports diverse crops. MSMEs in this sector can include paddy milling, spice processing (turmeric, ginger, chili), fruit pulp/jam production, and cold storage facilities. These ventures enhance agricultural value chains, reduce wastage, and provide better income for farmers, fostering rural prosperity. With an abundance of livestock farming and fisheries, western Odisha has untapped potential in food and dairy processing. MSMEs focused on milk chilling plants, paneer and ghee production, sweets manufacturing, and processed fish products can cater to growing consumer demand. These initiatives will strengthen rural economies and create employment in food processing industries.

Handloom & Handicrafts: Bargarh and Sambalpur are renowned for their Sambalpuri textiles, with artisans possessing remarkable weaving skills. MSMEs can modernize traditional weaving units, support natural dye production, and develop online selling platforms for local artisans. With growing global demand for handmade, eco-friendly products, this sector presents a promising avenue for economic growth.

Forest-Based Products: The forest-rich districts of Sundargarh and Balangir provide opportunities for sustainable enterprises such as lac cultivation, honey collection and processing, and bamboo-based products (furniture, crafts). These MSMEs promote the sustainable use of natural resources while empowering tribal communities with stable income sources.

Mineral & Metal-Based MSMEs: Western Odisha, particularly Jharsuguda and Sundargarh, is rich in minerals. MSMEs in fly ash brick production, stone crushing, and steel-based fabrication can leverage locally available raw materials. This not only reduces dependency on external industries but also fosters regional industrial growth and job creation.

Rural Tourism & Hospitality: The region boasts picturesque locations such as Hirakud Dam, Debrigarh Sanctuary, and Nrusinghanath Temple. MSMEs can capitalize on eco-tourism homestays, adventure tourism, and local cuisine restaurants. Tourism stimulates multiple sectors, including hospitality, handicrafts, and transportation, thereby generating widespread employment opportunities.

Renewable Energy & Green Solutions: With increasing emphasis on sustainability, MSMEs in solar panel assembly and installation, biomass briquette production (from agricultural waste), and LED manufacturing can thrive. Government incentives for green energy and rising energy demands make this sector highly viable for long-term growth.

MSMEs aligned with Western Odisha's unique resources and market demands can drive inclusive economic development, reduce migration, and empower local communities. By investing in agriculture, handloom, forest-based industries, minerals, food processing, tourism, and renewable energy, the region can create sustainable livelihoods and enhance economic resilience. Strengthening MSMEs through financial support, skill development, and infrastructure improvements will be key to unlocking Western Odisha's economic potential.

2.3 Employment Potential of MSMEs in Western Odisha Districts

The results of Karl Pearson's correlation, as presented in Table 1, indicate a significant positive association among the variables. It also demonstrates that MSME unit's growth has the high degree of positive relation with employment, while investment in MSMEs has the next strongest correlation with employment. On the other hand, investment and MSME units have the 0.83 degrees of correlation.

Table 1: Results of Correlation Matrix

Correlation Probability	Employment	Units	Investment
Employment	1.00000		
Units	0.941546 (0.0000)	1.00000	
Investment	0.899753 (0.0000)	0.831671 (0.0000)	1.00000

Source: Authors' estimations.

The panel data analysis can be done through Pooled/panel Ordinary Least Square (POLS), Fixed effect model (FEM) and Random effect model (REM). The POLS model assumes that all entities in the panel data have same intercept (5Ø6ß) while FEM considers difference in intercept for all entities in the panel due to different factors. But in REM it is assumed that the difference in intercept for all entities is due to randomness of sample.

In order to know which model is appropriate or the intercept of studied districts are same or different, first we have used the POLS technique in the panel data and then applied Breusch-Pagan test through Lagrange Multiplier Test for random effects. The obtained P value (0.00) of Breusch-Pagan test indicates that the null hypothesis of no effect or no different intercept is rejected. It defines the intercept of all studied districts are not same which allows us to run Random effect model rather than POLS.

Table 2: Result of Panel EGLS (Cross Section Random Effect)

Dependent Variable (Employment)			
Independent Variables	Coefficient	T-Statistics	Prob.
C	02.31	19.64	0.0000
Units	0.5417	19.34	0.0000**
Investment	0.2408	9.81	0.0000**
Adjusted R-squared	0.9349		
Durbin-Watson stat			

Source: Authors' estimations.

Notes: *, ** and *** represent the significance at 1per cent, 5 per cent and 10 per cent level respectively.

It is observed from REM test result (Table 2) that one per cent increase in number of MSME creates 0.54 per cent of additional employment whereas one per cent rise in investment generates 0.24 per cent of employment in MSME sector. After getting the result of REM, we run the Hausman test to make choice between REM and FEM regression. The null hypothesis of Hausman test is that the FEM and REM estimators do not have significance difference. The rejection of the null hypothesis indicates that the Fixed Effect estimator is a more suitable or appropriate for analysis of panel data (Abdullah et al., 2022). As in Table 3, the P value (0.49) is more than 0.05 so we cannot reject the null hypothesis. So, it is recognized that the REM regression is an appropriate model for the data set.

Table 3: Result of Hausman Test

Test Summary	Chi-Sq. Statistics	Chi-Sq. d.f.	Prob.
Cross –Section random	1.400	2	0.4965**
Cross-Section random effects test comparisons			
Variable	Fixed	Random	Prob.
Units	0.5447	0.5417	0.2604**
Investment	0.2384	0.2408	0.5518**

Source: Authors' estimations.
Notes: *, ** and *** represent the significance at 1per cent, 5 per cent and 10 per cent level, respectively.

In this section the relationship between the variables on the long run is examined. The first step in this section is to test for the existence of unit roots in panel data. Table 4 and 5 depict the results from Levin, Lin & Chu test and Im, Pesaran and Shin W-stat Test. It indicates that all variables are stationary at first difference or I(1) in one per cent level of significance.

Table 4: Result of Unit Root Test- Levin, Lin & Chu Test

Variables	Levels I(0)	1st difference I(1)	Result
Unit	0.9993	0.0121*	I(1)
Investment	0.9889	0.0003*	I(1)
Employment	0.9965	0.0002*	I(1)

Source: Authors' estimations.
Notes: *, ** and *** represent the significance at 1per cent, 5 per cent and 10 per cent level, respectively.

Table 5: Unit Root Test- Im, Pesaran and Shin W-stat

Variables	Levels I(0)	1st difference I(1)	Result
Unit	1.0000	0.0025*	I(1)
Investment	0.9867	0.0000*	I(1)
Employment	0.9993	0.0000*	I(1)

Source: Same as in Table 1.

Note: Same as in Table 2.

Table 6 indicates that the Fisher Johansen panel cointegration test result for the given model. Here the result depicts that the P value (0.0054) of trace test and P value (0.0054) of max-eign test are less than 0.01(1 per cent level of significance). So, the null hypothesis of no cointegration among variables in long run is rejected, which provides evidence of existence of long run relationship among variables.

Table 6: Johansen Fisher Panel Cointegration Test (Between Employment, Unit and Investment)

Hypothesized No. of CE(s)	Fisher Stat.* (from trace test)	Prob.	Fisher Stat.* (from max-eign test)	Prob.
None	39.40	0.0010*	34.01	0.0054*
At most 1	17.88	0.3309	19.34	0.2513
At most 2	9.181	0.9058	9.181	0.9058

Source: Same as in Table 1.

Notes: *, ** and *** represent the significance at 1per cent, 5 per cent and 10 per cent level, respectively.

After the confirmation of the existence of long run relation among the variables in the study, the long run impacts of independent variables on dependent variable is estimated. In this light we use two types of estimation methods such as FMOLS and the DOLS models.

Table 7: Result of FMOLS and DOLS Model

Method	Variables	Coefficient	t-statistic	P-value (Prob)	Adjusted R-squared
FMOLS	Investment	0.2532	9.03	0.0000	0.9467
	Units	0.5218	16.67	0.0000	
DOLS	Investment	0.3081	5.71	0.0000	0.9455
	Units	0.4589	8.80	0.0000	

Source: Same as in Table 1.

Notes: Dependent variable: Employment and Independent Variables: Number of MSME Units and Investment. *, ** and *** represent the significance at 1per cent, 5 per cent and 10 per cent level, respectively.

Employment as the dependent variable in Table 7. For the FMOLS methods the result explores that investment and units exerts a positive and significant impact on Employment generation in MSMEs. It can be postulated that one per cent rise in investment there is 0.25 per cent rise in employment. In case of number of units it explores that it is significantly positive impact on employment in MSME means here one per cent rise in number of MSME unit can rise 0.52 per cent of employment.

Similarly, from DOLS result it found the same as one per cent rise in investment there is 0.30 per cent increase in Employment. It is also found that number of MSME units also significant positively impact on employment as one per cent rise in number of MSME units leads to 0.45 per cent rise in employment. From the residual diagnostics test, it is evident that there is no autocorrelation and the residuals of FMOLS and DOLS model are normally distributed. The probability values of autocorrelation is more than 0.05 and Jarque-Bera probability value of Histogram-Normality Test is 0.619 which is also more than 0.05 level of significance.

3. Conclusion

The expansion and strategic promotion of Micro, Small, and Medium Enterprises (MSMEs) in the western region of Odisha can play a pivotal role in curbing the persistent issue of labour out-migration. With high employment potential of MSMEs, fostering a robust ecosystem for their growth can generate sustainable livelihood opportunities within rural areas. To realize this potential, the state government must adopt a comprehensive policy framework that includes access to affordable credit, skill development programs tailored to local needs, infrastructure development, export facilitation and market linkage support. Special incentives for setting up agro-based, handicraft, and rural enterprises can also encourage entrepreneurship and attract local youth. By strengthening the MSME sector through such targeted interventions, the state can not only reduce dependency on migration but also drive inclusive and regionally balanced economic growth in Western Odisha.

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Research Note / Commentary / Perspectives

Assessment of Agricultural Technological Efficiency in Haryana: A DEA-Tobit Approach

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Abstract

Research and Development (R&D) activities in agriculture are widely acknowledged for influencing agricultural technical efficiency. However, the impact of influencing factors on technological efficiency and, in turn, agricultural R&D is less clear. This study investigates how financial factors, human resources, and investments in agricultural R&D affect technological efficiency and ultimately improve agricultural production in Haryana. Using statistical data from 22 districts between 2010 and 2023, the study employs the DEA-Tobit approach to analyze the key role of technology and science in agricultural technological efficiency. The study concludes that while the technical market environment and human resources have an insignificant impact on technical efficiency, targeted investments in R&D are crucial.

Keywords: Technical efficiency; Data Envelopment analysis; Tobit regression analysis.

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Introduction

Technological advancements have revolutionized productivity and efficiency across economic sectors, diverging from classical economic theory. In agriculture, particularly in agrarian economies like India, this transformation has progressed but has not yet achieved full efficiency (Ucak, 2015). Agricultural technology now extends beyond mechanization to include biological modifications, digital tools, and precision farming techniques, enhancing cost-effectiveness and production efficiency (Gaviglio et al., 2021).

Innovation plays a crucial role in sustaining this technological progress. Agricultural science and technological advancements are key drivers of sustainable agriculture, supporting high-quality growth (Yao, 2022). These innovations impact multiple agricultural inputs, such as fertilizers, pesticides, and seed technology, contributing to rural economic development. In India, modern agricultural technology was introduced in the mid-1960s (Byres, 1982), significantly transforming farm practices and increasing agricultural growth by 55% (Ministry of Agriculture and Farmers' Welfare, 2021).

Haryana is one of India's leading states in agricultural modernization, contributing significantly to the country's agricultural output through innovative farming methods (Agriculture Statistics, 2017). However, despite its overall efficiency, agricultural productivity varies across districts due to differences in technical and scale efficiency (Goyal et al., 2006). Studies have identified factors influencing technical efficiency in Haryana's agriculture sector, such as climate change (Mor, 2017; Singh, 2017) and access to institutional credit (Singh & Sharma, 2012). This highlights the need to examine district-level variations in technological efficiency to identify regions lagging in adoption and performance.

Scholars have extensively analyzed agricultural efficiency using Data Envelopment Analysis (DEA). Various studies have applied DEA to assess resource allocation, production efficiency, and technological adoption in different regions (Yao & Wu, 2022; Zhang et al., 2021; Zhou et al., 2022; Hao et al., 2021; Chaubey et al., 2022). Some studies have integrated the Tobit model to examine factors affecting technological efficiency (Kameni et al., 2022; Wu & Yao, 2022). While previous research has primarily focused on efficiency measurement, there remains a gap in understanding how multiple factors—such as investment, human resources, economic conditions, and environmental indicators—shape technological efficiency at the district level.

Objectives of the Study

This study aims to assess agricultural technological efficiency across Haryana's districts using an integrated DEA–Tobit approach. Specifically, it seeks to:

1. Examine whether technological efficiency remains stable across Haryana's agricultural sector.
2. Identify the impact of investment, human resources, economic environment, financial expenditure, and technical market conditions on technological inefficiency.

Using panel data from 2010 to 2023 for all 22 districts of Haryana, this study provides insights into district-level efficiency variations and contributes to policy discussions on enhancing agricultural productivity.

Methodology and Research Model

The DEA model is used to measure the efficiency of any industrial unit based on input and output variables. Introduced by Charnes et al. (1978), it evaluates the relative effectiveness of various Decision-Making Units (DMUs) within a given sample. The CCR model utilized in this study determines the efficiency of each DMU by enlarging the ratio of total weighted outputs tototal weighted inputs:

$$Efficiency = \frac{weighted \ \ sum \ of \ outputs}{weighted \ \ sum \ of \ \ inputs}$$

The DEA weights are determined by the condition that each DMU's ratio is not more than one. This makes it possible to combine several inputs and outputs into "virtual inputs" and "virtual outputs" without giving each one a specific weight. The DEA serves to determine which DMUs are effective and which are ineffective. DEA, a method that emphasizes efficient frontier, assesses a DMU's inefficiency by contrasting it with other DMUs that are deemed efficient rather than relying on statistical averages that might not be pertinent to the performance of a specific DMU. From a methodological standpoint, the DEA features are outlined throughthe CCR method. This framework has N numbers of DMUs, all converting I (inputs) into J (outputs). The number of inputs (I) can be smaller than, equal to, or larger than the number of outputs (J). To evaluate the efficiency within each DMU, a specific model is used:

$$\text{Max } e^0 = \frac{\sum_{J=1}^{J} u_j^o y_j^o}{\sum_{i=1}^{I} v_i^o x_i^o} \quad \ldots\ldots\ldots\ldots\ldots\ldots \tag{i}$$

Subject to

$$\frac{\sum_{J=1}^{J} u_j^o y_j^n}{\sum_{i=1}^{i} v^o x_j^n} \leq 1; n = 1, \ldots\ldots N$$

$$v_i^o, u_j^o \geq 0; i = 1 \ldots\ldots I : j = 1 \ldots\ldots J$$

where y_j^n, x_j^n are positive known outputs and inputs of n^{th} DMU and v_i^o, u_j^o are variable weights to be determined by solving (i) efficiency ratio e^0=1, which satisfies the criteria for DEA's efficiency; nonetheless, DEA is inefficient. The problem is challenging to interpret in its original form due to the non-linear and fractional nature of the objective function. However, Charnes et al. (1978) converted this non-linear issue into linear by introducing a transformation, as shown below:

$$\text{Max } h^0 = \sum_{j=1}^{j} u_j^o y_j^o \quad \ldots\ldots\ldots\ldots (2)$$

Subject to

$$\sum_{i=1}^{J} v_j^o x_i^o = 1, \sum_{j=1}^{J} u_j^o x_j^n - \sum v^0 x_j^n \leq 0; n = 1 \ldots\ldots\ldots N$$

$$v_i^o \geq \sum, u_j^o \geq \sum, i = 1..I, j = 1 \ldots\ldots J$$

DEA modelingallows the analyst to select inputs and outputs with a managerial target. However, it has several limits. The DMUs recognized as efficient are only efficient with respect to others in the sample. It may be possible for a unit outside the sample to achieve greater efficiency than the best practice DMU in the sample. This study utilizes an output-based on variable scale compensation approach to assess the agricultural technological efficiency of 22 districts in Haryana from 2010 to 2022, aiming to calculate the efficiency of innovation. The reason for using output-based variable scale compensation is that the nature of input and output variables in agricultural technology and science are scaled (Yue, 2019). Since technological progress and efficiency are dynamic, this paper employs the DEA-Malmquist productivity model to break down technological advancements (Coelli, 2008).

The concept of DMUs is similar to that of entities, where each entity is evaluated as part of a group that utilizes inputs to produce outputs. The efficiency score resulting from the measurement ranges from 0 to 1, reflecting the degree of efficiency of the DMUs. DMU is considered efficient if it achieves a ratio of 1. Otherwise, when the model involves censored data, using Ordinary Least Squares (OLS) for parameter estimation may lead to inconsistent results. To address this issue, the paper employed the DEA-Tobit method focused on the Maximum Likelihood Method (MLE) to analyze the components influencing the efficacy of technological innovation in agriculture in Haryana district.Tobit model (Tobin, 1958) suggested the equation as follows:

$$I_i^* = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \ldots\ldots\ldots\ B_k X_{ik} + \varepsilon_i \quad {}_i \sim N(0, \sigma^2)$$

Where:

I_i^* = latent (unobserved) dependent variable

I_i = observed dependent variable, which follows:

$$I_i = \begin{cases} I_i^* & if\ I_i^* > 0 \\ 0, & \text{if } I_i^* \leq 0 \end{cases}$$

X_{i1}, X_{i2}, ……..X_{ik}= independent variables (predictors)

β_0, β_1,………….. β_k= parameters to be estimated

$_i$ = normally distributed error term with mean zero and variance σ^2.

depicts the efficiency ratio vector measured by the DEA-BCC model. This study examines five key factors that impact the situation: financial spending, the technological market landscape, the human capital available for innovation, investments, and the economic context.

Financial spending represents the local government's fiscal outlay and its influence on fiscal spending. Regarding the technological market landscape, we analyze the local patent grants during the specified time frame. Human resources are pivotal in technological innovation, so we assess the total R&D workforce. Expenditure on research and development and per capita GDP will indicate investment in science & technology and innovation in agricultural technological tools, respectively.

2.2. Variables and data selection

Based on agricultural production component theory, agricultural production inputs are land, labor, and capital. This paper considers these as inputs for the DEA, and based on the literature, output variables are total output produced, animal husbandry, and fishery. The cultivating portion of crops in each district is the input for land, and the total number of agriculture workers is used as input for labor. Agricultural machinery and agricultural fertilizer amount represent capital investment, and expenditure on R&D is the technological investment in our model. Data has been fetched from the Statistical Abstracts of Haryana, Annual Reports of the Ministry of Agriculture and Farmers' Welfare, Economic Surveys of Haryana, and the Finance Department of Government of Haryana.

2. Results and Discussion

To find the efficiency of factor inputs and outputs, comprehensive efficiency is represented by a single overall indicator. Comprehensive efficiency results from multiplying two types of efficiencies: scale efficiency and pure technical efficiency. DEAP 2.1 software has been used to calculate the outcomes from2010 to 2023for the 22 districts of Haryana. Table 1 presents the efficiency of agricultural scienceand technological innovation for the period. The districts of Faridabad, Panipat, and Gurugram demonstrate the highest levels of innovation efficiency in agriculture. From the perspective of the TFP index, 70 per cent of comprehensive efficiency values exceed 0.9, showing a generally high level of technological innovation in agricultural science efficiency in Haryana. Three districts – Gurugram, Hisar, and Panipat – are scale efficient with a value of 1, suggesting that the scale of technological innovation may be insufficient. Regarding regional disparities, the standard deviation of the comprehensive efficiency values for technological innovation across districts is 0.08, indicating a minimal gap. Overall, technological innovation in Haryana has progressed significantly in agricultural science, supported by progressive policies related to R&D in agricultural activities and increased investments in agricultural research and technology.

Table 1: Agricultural Science and Technological Innovation Efficiency from 2010 to 2023

Districts	TDF (Total factor Production Index)	EC (Technical Efficiency)	Scale Efficiency
Ambala	0.9725	0.9528	0.9825
Bhiwani	0.9025	0.9268	0.8836
Charkhi Dadri	0.9015	0.9358	0.9252
Faridabad	1	0.9875	0.9856
Fatehabad	0.9255	1	0.9452
Gurugram	1	1	1
Hisar	0.9625	0.9896	1
Jhajjar	0.9215	0.9739	0.9752
Jind	0.9325	0.9250	0.9135
Kaithal	0.9250	0.9386	0.9265
Karnal	0.9585	0.9725	0.9765
Kurukshetra	0.9225	0.9378	0.9258
Mahendragarh	0.8925	0.9125	0.8965
Nuh	0.8950	0.9125	0.9456
Palwal	0.9670	0.9737	0.9852
Panchkula	0.9525	1	0.9685
Panipat	1	1	1
Rewari	0.9425	0.9569	0.9685
Rohtak	0.9325	0.9536	0.9252
Sirsa	0.9425	0.9725	0.9586
Sonipat	0.9250	0.9368	0.9568
Yamunanagar	0.9680	0.9925	0.9982
Mean	0.9582	0.9725	0.9786

Source: Authors' calculations.

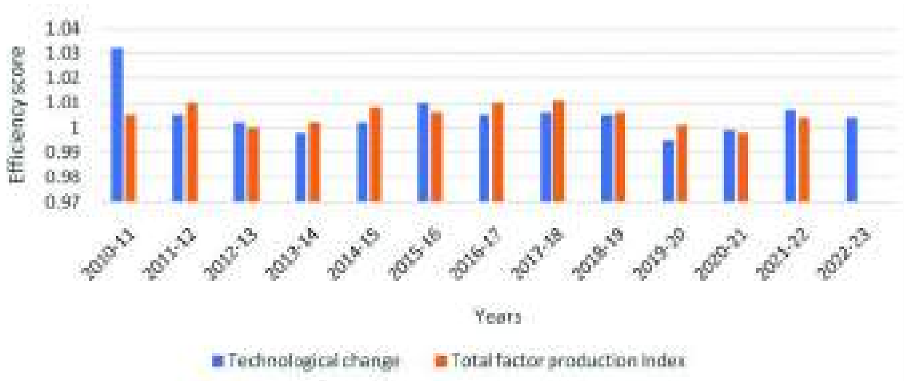
Table 2 exhibits the outcomes of the Malmquist Index and decomposition of technological innovation in agricultural efficiency in Haryana's districts (2010-23). A time series trend analysis reveals that total factor productivity for technological innovation in agricultural science in Haryana increased by 1.6 per cent between 2010 and 2023, with a 1.2% rise in technical efficiency. This suggests that the state's efficiency has experienced steady growth, driven by various factors of technological progress. Figure 1 shows that the Malmquist Index has remained stable, highlighting the efficiency of technological innovation in agricultural science in Haryana, which has continuously improved.

Table 2: Malmquist Index of Agricultural Science and Technological Innovation Efficiency in Haryana Districts from 2010 to 2023

Years	Technological change	Total FactorProduction Index
2010-11	1.032	1.005
2011-12	1.005	1.010
2012-13	1.002	1.000
2013-14	0.998	1.002
2014-15	1.002	1.008
2015-16	1.010	1.006
2016-17	1.005	1.010
2017-18	1.006	1.011
2018-19	1.005	1.006
2019-20	0.995	1.001
2020-21	0.999	0.998
2021-22	1.007	1.004
2022-23	1.004	1.002
Mean	1.012	1.016

Source: Authors' calculations

Figure 1: Malmquist Index of Agricultural Science and Technological Innovation Efficiency of Haryana State



Tobit Analysis of the Factors Affecting Agricultural Science and Technological Innovation Efficiency

The Tobit model is used to evaluate the components affecting the effectiveness of technological innovation in agricultural science in Haryana state. The following equation is formulated to identify the factors:

$$Y_{it}^{*} = \alpha + \mu_i + \beta X_{it}^{*} + \varepsilon$$

where Y_{it}^{*} is the score of DEA results. Ranging between 0 and 1, a score zero is least efficient, and score one indicates the most efficient unit. μ_i exhibits individual effect, X_{it}^{*} stands for determining factor and ε refers to the disturbance term. For the reduction of heteroscedasticity, a problem log of all independent variables has been taken. In this study, five major indicators of influencing factors are considered: financial expenditure, technology market environment, human capital, investment, and economic environment.

Financial expenditure is the investment in fiscal expenditure by local governments. It is considered as a key influencing factor for fiscal expenditure. The technology market environment, particularly local patent granted during the specified period, is considered as an influencing factor in technological innovation. Since human resources are the major source of development in technological innovation, total manpower in R&D personnel is considered for the same. Expenditure on R&D and per capita GDP are considered as proxy variables for investment in science and technology and innovation of agricultural technological instruments respectively.

Table 3: DEA-Tobit Model Results

Influencing factors	Co-efficient	Standard Deviation	t-value	p-value
Investment	0.168***	0.437	4.028	0.0001
Human Resources	0.0245	0.411	0.702	0.324
Economic Environment	0.185***	0.306	6.257	0.00023
Financial Expenditure	0.052**	0.252	2.145	0.023
Technical Market Environment	-0.00521	0.015	-0.525	0.425
Constant	0.325	0.215	1.525	0.145

Source: Authors' calculations

Notes: *** and** represent statistically significant at 1% and 5% level.

From Table 3, it may be concluded that technical market environment and human resources have insignificant influence on the effectiveness of technological innovation in agricultural science. However, the remaining explanatory variables impact significantly. Investment in science and technology improves by 0.00168 per cent, the economic environment factor increases the final output values of GDP by 0.00185 per cent, financial rises by 0.00052 per cent, agricultural science and technological efficiency rises by 1 unit. Although patent authorizations have increased in the state, they are happening in non-agricultural technology patents. It is explicit that financial investment plays a major role in agricultural technological R&D and the state's agronomy process.

Conclusion

Technological innovation in agricultural science efficiency implies the ability of farmers to enhance the level of farm production with the given resources or with the lesser inputs used. This study focuses on carrying out efficiency accounting by using two-stage DEA. The study reveals that Haryana exhibits relatively high overall technical efficiency, with only minor regional variations, but an insufficient scale effect exists. There is a need to allocate elements in the farm produce process. Improvement in technical elements indicates better agricultural productivity with fewer inputs. Districts with lesser efficiency scores can be improvedif the government focuses on them by infusing money and introducing and promoting innovative ideas in agricultural sciences. The agricultural technological improvement factor should be a key aspect of development and can be achieved if the government incurs expenditure on agriculture-related R&D. The deployment of AI technology can help make green and sustainable agriculture. Therefore, a double-pronged strategy is the need of the hour, where the required resources should be provided to farmers to enhance technical efficiency, along with the deployment of AI to improve productivity to cope with climate change (Mor, Madan & Prasad, 2021).

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Book Review

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Youth in Indian Labour Market: Issues, Challenges and Policies,
Edited by Arup Mitra,
Springer Nature, Singapore, 2024; pp. 290.

Keshab Das

Creation of adequate job opportunities for the Indian youth has continued to remain a huge challenge for the policy makers in India. Job search by the youth often starts too early without acquiring the requisite skills (as the market would demand or absorb) often driven by economic distress faced by them at the family level. The larger reason, however, remains the lack of infrastructure (physical, social and economic) in several regions (especially, the rural areas and the small and medium towns) which dents possibilities of 'local' employment and income generation. The rise of the so-called 'demographic dividend' or 'demographic advantage' also has implied the large presence of working-age youth who do not possess relevant skills or education as would be required by the labour market. The post-pandemic economic recovery has been slow and has constricted possibilities for new and more jobs for the youth.

An additional concern has been the fast-changing disruptive technology domain that has enhanced mechanization, automation and capital-intensive processes of both production and services. This has also implied that several low-end 'technical' or 'engineering' jobs are no longer required by the potential employers. Skilling, reskilling and upgrading skill sets in these new technology spheres has been difficult to organize and afford both for the state as well as individual firms.

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It is in this broad context that the volume edited by Arup Mitra assumes significance. With a collection of thirteen articles, the volume addresses job issues amongst youth across subsector (mainly agriculture), social identities and gender. The initial section deals with national and global perspectives on youth unemployment bringing out critical role played by absence of or low levels of skill mostly among relatively younger in the cohort. In the global review, as in the second chapter, it is clear that targeting skills alone through policy might not matter much in the absence investments in economic activities, particularly, infrastructure. The distortion of the labour market as deeply influenced by caste, rurality and low-income family background has been brought out using official statistics. Globally, as this chapter argues, youth employment and income are affected by aspects as educational and/or skill levels, where they are located and the gender.

In the Indian context, even when youth employment is recorded the informal and casual nature of the jobs raise questions about income security and social security benefits that one associates with regular employment. Another chapter focuses on the plight of the youth (in the age group of 15 to 29 years) and points to the fact that even during the pre-pandemic phase their participation in the labour market was low and this was particularly worrisome for females who often fell into the dismal category of NEET or, ‘Not in Education, Employment, or Training’. Preference for the more experienced at 30+ age group was obvious.

The following two sections comprising four articles, bring to the fore a variety of insecurities plaguing a large proportion of youth, particularly, concerning education and job mismatch and women from lower income households finding it difficult to access regular and secured jobs. One chapter focusing on Uttar Pradesh, finds a mixed scenario for youth in employment. For instance, while the incidence of written contracts seems to risen for women that has not been matched by an increase in social security benefits. Another chapter that has analysed data on formal education and occupational opportunities points to the discouraging situation where despite an improvement in educational attainment by the youth (as compared to their elders) in a slum in Delhi work participation rates seemed higher for those not in education. Also, there have been an emergence of low-skilled activities in which the youth performed an auxiliary role in modern services as computer operators, assistant accountants and assistants in chartered accountancy firms. This study hints at rethinking education and skilling programmes for the youth to be in demand in the changing labour market especially in urban areas.

A chapter focusing on women employment scenario over the decades point to the low-income occupations of working in the farmlands, homebased enterprises and domestic help that engaged rural women, in particular. Any industries that required endowment of higher skills would not find women suitable to join. More disturbing is the observation, “However, recent empirical evidence shows that many young women all over India, irrespective of states, are doing nothing, implying early entry in domestic duties” (p. 162). Similar lye, one more chapter with a gender concern observes the relatively low female work participation rates and prevalence of high unemployment amongst young women in urban India. Even the share of young women in NEET remains high and these are often found engaged in the domestic activities without earning any income. The author also expresses concern over the decline in the quality of jobs in the salaried categories as well.

Three clearly disjointed chapters have been clubbed in Section titled ‘Agriculture, Climate Change and Migration’ discuss youth employment issues from diverse perspectives. One chapter that analyses the migrant workers (mostly from Bihar and Jharkhand) in agriculture in the two once-Green-Revolution-driven prosperous states of Punjab and Haryana observes “While material inputs are losing productive value and sustain ability in the western high production states of India, the marginal productivity of labour remains positive and high in all states though higher in the eastern states contesting any claim of disguised unemployment” (p. 211). Investing in agriculture in eastern India might create better opportunities for youth there, it is implied. In another study, drawing upon field survey in rural Tamil Nadu,the author argues for increasing investment in irrigation infrastructure (both ground and micro, as the situation requires) to promote local farming potential that would prevent distress migration particularly from rainfed areas to urban areas.The third chapter in this section attempts estimates of jobs for youth (through three distinct situations) in the difficult (if not unlikely) event of India moving over to a clean climate regime. As the author envisages the future of demand for youth employment, “Employment in the conventional energy sector will be reduced while the employment generated in the renewable energy sector is expected to more than compensate for the loss of jobs in the traditional energy sectors. This will create an enormous opportunity for the skilled youth in India" (p. 238). Youth in particular, as the author underscores, need to reskill themselves so as to be relevant for the changing technology setting; as for instance, those in the non-renewable energy sector should prepare for joining the emerging renewable energy sector.

One of the two chapters in the last section on policy, though not focused on youth employment issues, questions both the labour and education policies in India over the decades as during 1950 to 2000s which, ultimately, was akin to a 'low-road' strategy where over 90 per cent of workers toiled in the informal sector. With gross neglect of primary education for long access to higher education and skills remained beyond the purview of many. Moreover, the clamour by big capital to relax labour regulations further undercuts both labour rights and opportunities that could be available to the youth, in general. The author makes an intent case for considering an all-encompassing social policy as integral to employment policies being devised by the state. The last chapter in this section and of the volume engages with the somewhat neglected question of relevance of and access to vocational education and skill training (VET) as often made available through formal/state channels. The authorsobserves that "The formal vocational training access among the youth is concentrated in the higher expenditure quintile, and among those with higher education levels… The youth from poorer and underprivileged backgrounds seem to be unable to afford formal VET (p. 288)". Given formal VET's various low points, the authors bring up the aspect of growing demand for training from informal channels even as for the youth it has meant low productivity and concomitant poor income. A serious relook at these issues would help address the challenge of preparedness of youth to join the labour market in future with requisite skill and receive a decent income.

The book, though includes some interesting papers appears to have been finalized in a haste and is in a disarray in terms of organization. The sections (or, for that matter, individual chapters therein) are scattered and not properly/adequately titled (for instance, two sections titled as "Specific Context" and "Policy Focus") fail to maintain any continuity or links as often youth employment remains subsumed under overall unemployment problem. Further, there is (rather surprisingly) little one could understand about the crisis of youth unemployment with reference to manufacturing subsectors and, importantly, services. There is virtually no discussion on the rise of the information and communication technology and new challenges as posed by the fast growth of e-commerce and platform or gig economy. The volume hardly discusses issues in infrastructure as these affect prospects of youth employment across space and subsectors. A specific concern with several chapters in this volume as also the general scholarship is concerned has been that little effort is being made to make a trip to the field for primary data collection and to have a brush with ground reality. An excessive dependence on large scale national survey data by most labour/ employment scholars in India constricts possibilities of rich insights that could be obtained from micro studies.

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