Cover Letter

Dr. Jadhav Chakradhar
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[26/08/2026]

Selection Committee

Workshop on Development Economics and Networks for Early-Career Researchers
National Bureau of Economic Research (NBER)

Subject: Application for the Workshop on Development Economics and Networks for Early-Career Researchers

Dear Members of the Selection Committee,

I am writing to apply for the **Workshop on Development Economics and Networks for Early-Career Researchers**. My research broadly focuses on development economics, with interests in poverty and inequality, labour markets, education, gender, and the socioeconomic processes that shape human development in India. I am particularly interested in understanding how disadvantages accumulate across different dimensions of life and how these disadvantages translate into unequal economic and educational opportunities.

My current research project, **"Child Deprivation and Early Educational Outcomes: Evidence from India,"** uses longitudinal data from the Young Lives study to examine how multidimensional deprivation during childhood affects school participation and subsequent learning outcomes. Using the Younger Cohort of Young Lives India across multiple survey rounds, the study constructs a child-specific multidimensional deprivation measure covering health, education, and living standards, following the Alkire–Foster framework. The longitudinal structure of the data allows me to examine how early-life disadvantages translate into later educational outcomes rather than treating deprivation and educational attainment as purely contemporaneous phenomena.

The study goes beyond conventional monetary measures of poverty by examining overlapping disadvantages in children's health, parental education, nutrition, and household living conditions. I investigate their relationship with both initial school enrolment and subsequent learning outcomes, using standardized measures of mathematics, language, and cognitive achievement. The empirical strategy also incorporates rare-event logistic models and instrumental-variable and control-function approaches to address issues of endogeneity and causal identification.

An important aspect of my research is the examination of heterogeneity and social structure. The analysis shows that the effects of multidimensional deprivation are not uniform: girls, rural

children, and children from socially disadvantaged groups experience substantially larger educational penalties. In particular, the intersection of gender, caste, religion, and deprivation provides an important lens through which to understand unequal educational trajectories. The Young Lives data are especially valuable in this respect because they allow early-life conditions to be linked with subsequent outcomes at the child level over time.

I see the workshop as an important opportunity to develop this research further. While my current work primarily examines multidimensional deprivation and its consequences, I am increasingly interested in how social networks, household relationships, community structures, and access to information and resources mediate the transmission of disadvantage. The workshop would therefore help me connect my existing research on poverty, education, and inequality with the growing literature on networks in development economics. I would particularly value feedback on how network mechanisms and social interactions can be incorporated into future research using longitudinal data from developing-country contexts.

I also hope that participation in the workshop will expose me to new empirical strategies and allow me to engage with other early-career researchers working on related questions. The opportunity to receive feedback from researchers working at the intersection of development economics and networks would be particularly valuable for strengthening my current research agenda and developing new collaborative research projects.

If shortlisted, I would be pleased to provide a recommendation from:

Prof. E. Revathi
Professor and Director
Centre for Economic and Social Studies (CESS)
Hyderabad, India
Email: revathi@cess.ac.in

Thank you for considering my application. I would be grateful for the opportunity to participate in the workshop and contribute to the discussions.

Sincerely,

Dr. Jadhav Chakradhar
Centre for Economic and Social Studies (CESS)
Hyderabad, Telangana, India
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Curriculum Vitae

Dr. Jadhav Chakradhar

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Areas of Interest

- **International Trade:** Trade in agriculture, trade costs, regional trade agreements, fisheries subsidies
- **Labour Markets:** Inequalities in employment, caste affiliation and labour outcomes
- **Macroeconomics and Trade:** Economic and policy uncertainty, trade flows, and EPU

Current and Completed PhD courses

- Methodology of Research in Social Science
- Perspectives in Social and Economic Change
- Basic Econometrics
- Advanced Econometrics
- Production Economics
- Agricultural Economics
- Microeconomic Theory
- Macroeconomic Theory
- Development Economics
- Agricultural Economics – II
- Data Bases in Agricultural Economics
- Self Study: Emergence of Cluster Groups and International Trade: A Review of Existing Studies
- Self Study: International Trade and Agglomeration
- **BREAD Course on Political Economy and Development** – September 08 to November 24, 2026

Submitted and Ongoing Projects

Diversity in the Indian Labour Market: Evidence from Indian Manufacturing Industry
Funding Agency: ICSSR, New Delhi, India *Status:* Submitted

Second Round of Social Audit of PM POSHAN in Selected Schools across 33 Districts of Telangana
Funding Agency: Director, School Education, Government of Telangana, India *Status:* Submitted

Third Round of Social Audit of PM POSHAN in Selected Schools across 33 Districts of

Telangana
Funding Agency: Director, School Education, Government of Telangana, India *Status:* Submitted

Telangana Socio-Economic, Education, Employment, Political and Caste (Comprehensive Household) Survey 2024 (TGSEEEPCS 2024)
Funding Agency: Planning Department, Government of Telangana *Status:* Submitted

Young Lives (YL) Round 7 – Longitudinal Study of Poverty and Inequality
Funding Agency: Department for International Development (DFID) *Status:* Submitted

Enhancing Export Potential of AYUSH Products for Global Well-being: Strategies and Opportunities
Funding Agency: ICSSR, New Delhi, India *Status:* Submitted

Study on Chemical Fertilizers Consumption in Andhra Pradesh (2024)
Funding Agency: Rythu Sadhikara Samstha (RySS), Government of Andhra Pradesh, India *Status:* Submitted

Internal Police Reform in India
Funding Agency: Indian Police Foundation (IPF), New Delhi *Status:* Ongoing

Fourth Round of Social Audit of PM POSHAN in Selected Schools across 33 Districts of Telangana
Funding Agency: Director, School Education, Government of Telangana, India *Status:* Submitted

Educational Qualifications

Ph.D. in Economics
Institute for Social and Economic Change (ISEC), Bangalore, India
Thesis: "Trade Agglomerations: Genesis and Determinants"
Supervisor: Dr. A.V. Manjunatha
Doctoral Committee

- Prof. R.S. Deshpande (Former Director, ISEC)
- B.P. Vani (Associate Professor, CESP, ISEC)
- Dr. Malini L. Tantri (Associate Professor, CESP, ISEC)

M.A. in Applied Economics
Pondicherry Central University, Pondicherry, India

B.A. in Economics
Silver Jubilee Government College (SJGC), Kurnool, Andhra Pradesh, India

Professional Experience

Assistant Professor in Economics *April 2019 – Present*
Centre for Economic and Social Studies (CESS), Hyderabad

Visiting Faculty *August 2018 – March 2019*
Centre for Development Studies (CDS), PES University, Bangalore

Research Associate *November 2013 – August 2014*
Indian Institute of Management, Bangalore (IIMB)

Research Assistant *October 2012 – October 2013*

Washington State University, USA (with Dr. Andrew Flachs)

Resource Person Engagements

1. Invited as a resource person at the ESCAP/ISO/UNCTAD Workshop on *Non-Tariff Measures and International Standards for Sustainable Development*, held on March 13–14, 2019, in Bangkok, Thailand.
2. Invited as a resource person for the training program on *Evidence-Based Trade Policy Making for Sustainable Development*, organized by UNCTAD/ESCAP-ARTNet, from November 26–30, 2018, in Bangkok, Thailand.
3. Delivered an online lecture on the theoretical and practical applications of the gravity model to MA Business Economics students, Department of Data Science, Christ (Deemed to be University), Lavasa, Maharashtra, India, May 11–14, 2021.
4. Delivered a lecture on career counseling for the Class of 2022 at Jawahar Navodaya Vidyalaya (JNV), Landiguda, Koraput (Odisha), July 31, 2022.
5. Invited as a Discussant at the parallel session of the *17th Bulletin of Monetary Economics and Banking International Conference* on *Synergy and Innovations in Strengthening Resilience and Economic Revival*, organized by Bank Indonesia Institute, September 16, 2023.
6. Delivered a lecture at Punjab Agricultural University (PAU) on *Women Empowerment and Labor Market Discrimination*, September 19, 2023.
7. Delivered 10 lectures on Applied Micro and Macroeconomics to M.A. Public Policy students, Department of Public Policy, Manipal Academy of Higher Education (MAHE), Bengaluru campus, September 21–29, 2023.
8. Invited as a Discussant for the panel discussion on *Digital Inclusion and Exclusion* at the 19th IUAES WAU World Anthropology Post Congress Conference 2023, themed *Anthropology and Digital Cultures*, hosted by the Department of Anthropology, University of Hyderabad, October 26–27, 2023.
9. Delivered a lecture on *Research Ethics, Plagiarism, and Referencing* during a ten-day virtual Research Methodology Workshop sponsored by ICSSR-WRC, March 1–13, 2024. Organized by Mahatma Night Degree College of Arts and Commerce, University of Mumbai.
10. Delivered 12 lectures on *Advanced Macroeconomics II* to MSc (Economics) students, Symbiosis School of Online and Digital Learning, Symbiosis International (Deemed University), Pune campus, April 26–June 13, 2024.
11. Delivered a guest lecture on *Small Open Economies & the Mundell-Fleming Model*, organized by the School of Social Sciences & Humanities (VISH), VIT-AP University, Amaravati, India, June 1, 2024.
12. Invited as a Session Chair at the Second International Conference on Innovations in Infrastructure (ICIIF 24), organized by the Institute of Infrastructure Technology Research and Management (IITRAM), Ahmedabad, November 15–17, 2024.
13. Invited as a Session Chair for the international conference *AYUSHGLOBE 2025: AYUSH for Global Well-Being and Exports from India*, held on January 31, 2025, at IITRAM, Ahmedabad.
14. Guest Lectures for Doctoral Students (DBA), Aston University, United Kingdom. Topics: t-tests, Correlation, ANOVA, Chi-Square, Linear Regression, Mediation & Moderation,

Multivariate Analysis. (December 2024 – continuing).

15. Delivered a special lecture on Theory and Application of the Gravity Model of Trade at the School of Economics, University of Hyderabad, on October 27, 2025.
16. Chaired a Technical Session at the Two-day International Conference on "Structural Change, Youth Employability, and Inequality", jointly organised by **School of Economics, University of Hyderabad**, **ICFAI School of Social Sciences, IFHE, Hyderabad**, and **Young Scholar Initiative (YSI)–INET, New York**, held on November 27–28, 2025, Hyderabad.
17. Delivered a Special Lecture on "Trade Policy Uncertainty in a Changing Global Order: Implications for India" at the Two-Day National Seminar on "Changing Tariffs – Implications for the World Trade System: Challenges and Opportunities for India and Asian Countries", organized by **A.V. College of Arts, Science & Commerce, Hyderabad**, in association with the **Institute of Asian Studies**, on January 27, 2026, Hyderabad.
18. Invited Resource Person: Delivered lectures on "Correlation and Regression Analysis" and "Regression Diagnostics Analysis" at the Ten-Day Research Methodology Course (RMC) for PhD/PDF Scholars in Social Sciences, sponsored by **ICSSR, New Delhi**, organized by the **Department of Economic Studies and Planning, Central University of Karnataka (CUK), Kalaburagi**, on March 20, 2026.

Recent Roles / Appointments

1. Research Progress Committee (RPC) Member of Mr. Saravanan Sengunthar, Institute of Infrastructure, Technology, Research and Management (IITRAM), Gujarat.
2. Subject Expert for Sivanthi S (MSc in Agricultural Economics), Department of Dairy Economics and Business Management, Guru Angad Dev Veterinary and Animal Sciences University (GADVASU), Ludhiana, Punjab.
3. Visiting Faculty, Department of Public Policy, Manipal Academy of Higher Education (MAHE), Bengaluru.
4. Member of Internal Protocol Advisory Committee (IPAC) for PhD scholar Saghar Ada, Manipal University, Bengaluru.
5. Convenor, Computer and Website Committee, Centre for Economic and Social Studies (CESS), Hyderabad (since 2020).
6. Member, Annual Report Committee, Centre for Economic and Social Studies (CESS), Hyderabad (since 2021).

Publications

Journal Articles (Including Working Papers)

1. Kumar, R., Kumar, R. R., Stauvermann, P. J., & Chakradhar, J. (2019). The effectiveness of fisheries subsidies as a trade policy tool to achieving Sustainable Development Goals at the WTO. *Marine Policy*, **100** (June), 132–140. https://doi.org/10.1016/j.marpol.2018.11.034. (Elsevier; ABDC: A; Scopus; Impact Factor: 4.173).
2. Kumar, R., & Chakradhar, J. (2019). An assessment of fishing vessel capacity on subsidies, non-tariff measures, and attaining Sustainable Development Goals. *ARTNeT Working Paper Series*, No. 184, May 2019. Bangkok: UN ESCAP. Link to paper.
3. Bairwa, A. K., Chakradhar, J., & Sharma, P. (2020). Employment Discrimination in Indian Manufacturing Industries: A Logit Analysis. *The Singapore Economic Review*, **65**(s1),

233–259. (SSCI; Scopus; ABDC: B). https://doi.org/10.1142/S021759081944003X.

4. Chakradhar, J., & Bairwa, A. K. (2020). Employment probabilities and workforce distribution in the Indian manufacturing sector: A state-level analysis. *Bulletin of Monetary Economics and Banking*, **23**(1), 55–82. (SSCI; Scopus; ABDC: B). https://doi.org/10.21098/bemp.v23i1.1293.
5. Kumar, R., Chakradhar, J., & Balchin, N. (2020). Unpacking the possible elements of a future Digital Trade Agreement on digitalization and economic growth: Insights from panel data analysis. *Policy Hackathon on Model Provisions for Trade in Times of Crisis and Pandemic in Regional and other Trade Agreements*. UN ESCAP. PDF.
6. Gupta, R., & Chakradhar, J. (2022). The consequences of mandatory corporate social responsibility expenditure: Empirical evidence from India. *Business and Society Review*, **127**(1), 49–68. (Wiley; Scopus; ABDC: C). https://doi.org/10.1111/basr.12251.
7. Chakradhar, J., & Thao, T. T. (2024). The Impact of Participating in the Regional Comprehensive Economic Partnership (RCEP) Agreement and Potential Export Markets for Vietnamese Rice: An Application of Augmented Gravity Model. *Journal of International Commerce, Economics and Policy*, **15**(02), 2450004. (ABDC: C; Scopus). https://doi.org/10.1142/S1793993324500042.
8. Chakradhar, J., & Manjunatha, A. V. (2024). Navigating the Shifting Tides: A Critical Assessment of International Trade Theory and Policy in the Era of Emerging Trade Agglomerations. *ISEC Working Paper No. 646*. Bengaluru: Institute for Social and Economic Change. Link.
9. Chakradhar, J., & Choudhary, P. K. (2024). Inequalities in Computer Literacy in India: Do Caste and Gender Matter? *Economic & Political Weekly*, Special Article. (ABDC: B; Scopus). Link.
10. Chakradhar, J., & Gupta, R. (2024). Heterogeneous Effect of Economic Policy Uncertainty on Firm Financial Performance: Empirical Evidence from India. *Managerial and Decision Economics*. (Wiley; ABDC: B; Scopus). https://doi.org/10.1002/mde.4308.
11. Bairwa, A. K., & Chakradhar, J. (2024). Caste Affiliation and Access to High-Authority Jobs in the Indian Service Sector. *Journal of the Asia Pacific Economy*, 1–27. (ABDC: B; Scopus). https://doi.org/10.1080/13547860.2024.2401220.
12. Chakradhar, J., Singh, J., & Renukunta, A. (2024). Linder Hypothesis and India's Services. *Economics and Business Review*, **10**(3). (ABDC: C; Scopus). https://doi.org/10.18559/ebr.2024.3.1045.
13. Chakradhar, J., & Manjunatha, A. (2025). *Assessing and Explaining Trade Agglomeration in the Context of Global Trade*. ISEC Working Paper No. 593. Link.
14. Padmaja, P., Chakradhar, J., & Revathi, E. (2025). Free Trade Agreements and Impact on Indian Turmeric Trade: A Partial Equilibrium Analysis. *Indian Journal of Agricultural Marketing*. Link.
15. Chakradhar, J., & Gupta, R. (2025). Corporate Social Responsibility and Firm Financial Performance: The Moderating Effect of Economic Policy Uncertainty. *Journal of International Commerce, Economics and Policy*. (Scopus Q2). https://doi.org/10.1142/S1793993325500139.
16. Kumar, P., Chakradhar, J., & Devendra, P. (2025). Dissemination of False Information and Societal Polarization: An Empirical Investigation. *Journal of Information Technology & Politics* (Taylor & Francis). (Scopus Q1). https://doi.org/10.1080/19331681.2025.2519053.

17. Ellanki, R., Chakradhar, J., & Reddy, P. P. (2025). *Education and Learning in Andhra Pradesh: Preliminary Findings from the 2023–24 Young Lives Round 7 Survey*. Young Lives Factsheet, May 2025. Centre for Economic and Social Studies (CESS) and Young Lives. Link.
18. Ellanki, R., Chakradhar, J., & Reddy, P. P. (2025). *Education and Learning in Telangana: Preliminary Findings from the 2023–24 Young Lives Round 7 Survey*. Young Lives Factsheet, May 2025. Centre for Economic and Social Studies (CESS) and Young Lives. Link.
19. Padmaja, P., Revathi, E., & Chakradhar, J. (2025). Determinants and Export Potential of India's Turmeric Exports: Evidence from an Augmented Panel Gravity Model. *IASSI Quarterly: Contributions to Indian Social Science*, **44**(3), 673–697. Link.
20. Chakradhar, J., Ganguly, A., Choudhury, R. N., & Jadhav, P. (2025). Trade policy uncertainty and agricultural exports: The mitigating roles of RTA and liberal democracies. *Transnational Corporations Review*, **17**, Article 200160. Link.
21. Arote, P., Sagara, H., Chakradhar, J., Desai, G., Pravin, J., & Bandhu, D. (2026). The impact of India–ASEAN free trade agreement on trade flows: An application of augmented gravity model. *PLoS One*, **21**(6), e0350036. Link.
22. Chakradhar, J., & Aditya, A. (2026). Growth under uncertainty: Heterogeneous impacts of economic policy shocks: Evidence from a panel quantile regression. *Economic Change and Restructuring*, **59**, 77. Link.
23. Chakradhar, J., Choudhary, P. K., & Bairwa, A. K. (2026). The role of liberal democracy and policy uncertainty in shaping economic growth: An empirical analysis. *Journal of Public Affairs*, **26**(2), e70125. Link.
24. Bairwa, A. K., & Chakradhar, J. (2026). Assessing social diversity progress in India's manufacturing: A quantitative study using a diversity index. *Economic and Political Weekly (EPW)*. Accepted for publication in the Special Article section.
25. Poola, D., Chakradhar, J., Kasarapu, S. S. K., & Choudhary, P. K. (2026). *Mapping cybersecurity literacy: Inequality, capability, and digital vulnerability in India*. *Humanities and Social Sciences Communications*. Link
26. Lee, J., Steare, T., Chakradhar, J., Ellanki, R., Wels, J., & Patalay, P. (2026). *The mental health impacts of child marriage in Ethiopia, India, Peru, and Vietnam: A longitudinal investigation*. *medRxiv*. Link
27. Choudhary, P. K., Chakradhar, J., & Poola, D. (2026). *Evidence on the relationship between democracy and sustainable development across income groups*. *Discover Environment*, 4, 338. https://doi.org/10.1007/s44274-026-00856-4 Link

Book Chapters

1. Chakradhar, J., & Choudhary, P. K. (2025). Digital inclusion and women development: Evidence from Indian states. In E. Revathi, S. Chandra, B. Suresh Reddy, & A. Madan (Eds.), *Intersecting Paths of Sustainable Development, Urbanization, and Women's Empowerment* (pp. 125–142). Springer. ISBN 978-981-97-9217-7.

Work in Progress (Book)

1. Chakradhar, J. *Trade Agglomerations: Genesis and Determinants*. Oxford University Press, India – Forthcoming.
2. Chakradhar, J., & Kumar, P. *Digital Inclusion and Caste Disparities: A Study of Computer Literacy in India*. Work in progress.

Articles Under Review

1. Chakradhar, J. Determinants and Export Potential of Indian Rice: An Application of Poisson Pseudo Maximum Likelihood and Heckman Gravity Approach. Submitted to *Millennial Asia: An International Journal of Asian Studies*. Manuscript ID: MLA-2024-0045.RV1.
2. Chakradhar, J., & Gupta, R. Does Economic and Policy Uncertainty Affect India's Trade Flow? Moderating the Role of Regional Trade Agreements. Submitted to *Studies in Economics and Finance (SEF)*. Manuscript ID: SEF-12-2023-0727.R1.
3. Kumar, P., & Chakradhar, J. (2025). Democratic Backsliding in South Asia: The Role of Disinformation, Hate Speech, and Polarization. Submitted to *Economic & Political Weekly*.

Articles in Progress

1. Chakradhar, J., & Maryam, J. Trade Policy Uncertainty and Economic Growth: Evidence from Impulse Response by Local Projection.
2. Chakradhar, J., & Jadhav, P. Determinants of Indian Service Exports with European Union (EU): Application of Generalized Least Squares (GLS).

Young Lives Project Papers

1. **Unequal Beginnings: A Capability-Based Measure of Early Life Poverty.** *with* Kaibalyapati Mishra, Revathi Ellanki, P. Prudhvikar Reddy,
2. **Child Deprivation and Early Educational Outcomes: Evidence from India.** *with* Kaibalyapati Mishra, Revathi Ellanki, P. Prudhvikar Reddy
3. **Childhood Deprivation and the Labour Force Participation of Young Adults: Causal Evidence from India.** *with* Kaibalyapati Mishra, Revathi Ellanki, P. Prudhvikar Reddy
4. **Does Childhood Deprivation Compress the Wage Floor? GPS Evidence on Reservation Wages of Young Indian Workers.** *with* Kaibalyapati Mishra, Revathi Ellanki, P. Prudhvikar Reddy
5. **What Jobs Do Young Indians Want and Can They Get Them? Willingness-to-Pay, Aspiration–Access Gaps, and Gender in a Discrete Choice Experiment.** *with* Kaibalyapati Mishra, Revathi Ellanki, P. Prudhvikar Reddy

Editorials and Opinion Pieces in Leading Newspapers

1. Chakradhar, J., & Kumar, R. (10 Aug 2018). Trump's tariff tantrums: will India benefit or lose? *Deccan Herald*. https://www.deccanherald.com/opinion/panorama/trumps-tariff-tantrums-will-686841.html
2. Chakradhar, J., & Bairwa, A. K. (18 Jan 2019). 10% reservation for general category: the fatal blow. *Deccan Herald*. https://www.deccanherald.com/opinion/fatal-blow-713571.html
3. Bairwa, A. K., & Chakradhar, J. (12 Feb 2019). Economics of reservation. *Telangana Today*. https://telanganatoday.com/economics-of-reservation
4. Chakradhar, J., & Medha, A. S. (23 May 2020). 20 lakh crore package: stimulus or frivolous? *Hans India*. https://www.thehansindia.com/hans/opinion/news-analysis/20-lakh-crore-package-stimulus-or-frivolous-624024
5. Sastry, K. L. N., & Chakradhar, J. (4 Nov 2022). India holds immense potential to emerge as an innovation leader. *The Pioneer*. https://www.dailypioneer.com/2022/state-editions/india-holds-immense-potential-to-emerge-as-innovation-leader.html

6. Chakradhar, J., & Bhushan, B. (5 Apr 2023). *In the Kingdom of Kubera, There Are More People Who Can't Join Together* (in Telugu). *Andhra Jyothi*. https://www.andhrajyothy.com/2023/editorial/in-the-kingdom-of-kubera-there-are-more-people-who-cant-join-together-1043409.html
7. Jadhav, P., & Chakradhar, J. (3 Aug 2023). India's rice export ban to upset global food security. *Policy Circle*. https://www.policycircle.org/opinion/rice-exports-ban-disrupts-market/
8. Chakradhar, J., Choudhary, P. K., & Nayak, J. M. (3 May 2023). Make India digitally inclusive. *Telangana Today*. https://telanganatoday.com/opinion-make-india-digitally-inclusive
9. Mishra, K., & Chakradhar, J. (11 Dec 2023). The entertainment–inequality nexus. *Telangana Today*. https://telanganatoday.com/opinion-the-entertainment-inequality-nexus
10. Choudhary, P. K., & Chakradhar, J. (8 Feb 2023). India's billionaires and billion others. *Deccan Herald*. https://www.deccanherald.com/opinion/in-perspective/india-s-billionaires-and-billion-others-1189321.html
11. Choudhary, P. K., & Chakradhar, J. (14 Nov 2023). Why Narayana Murthy is wrong. *Telangana Today*. https://telanganatoday.com/opinion-why-narayana-murthy-is-wrong
12. Chakradhar, J., & Bairwa, A. K. (14 Nov 2024). AI and income inequality. *Telangana Today*. https://telanganatoday.com/opinion-ai-and-income-inequality
13. Chakradhar, J., & Bairwa, A. K. (14 Nov 2024). AI's impact on global trade. *Telangana Today*. https://telanganatoday.com/opinion-ais-impact-on-global-trade
14. Choudhary, P. K., & Chakradhar, J. (6 Jan 2025). More money for bottom 50 percent. *Telangana Today*. https://telanganatoday.com/opinion-more-money-for-bottom-50
15. Poola, D., & Chakradhar, J. (14 Feb 2025). Short-term gain, long-term pain: roll back the freebie culture. *The New Indian Express*. https://www.newindianexpress.com/web-only/2025/Feb/14/short-term-gain-long-term-pain-time-to-roll-back-the-spread-of-freebie-culture
16. Sharma, C., Chakradhar, J., & Jadhav, P. (14 Feb 2025). Tax relief doesn't resolve structural issues. *Telangana Today*. https://telanganatoday.com/opinion-tax-relief-doesnt-resolve-structural-issues
17. Sharma, C., & Chakradhar, J. (19 Apr 2025). US tariffs raise stakes for Indian exporters – but open doors in select sectors. *Policy Circle*. https://www.policycircle.org/opinion/us-tariffs-raise-stakes-for-exporters/
18. Chakradhar, J., & Nayak, J. (25 Apr 2025). Will trade wars and fiscal austerity derail global growth? *Madras Courier*. https://madrascourier.com/opinion/will-trade-wars-fiscal-austerity-derail-global-growth/
19. Chakradhar, J., & Mishra, K. (28 Apr 2025). Services up, goods down: India eyes gains in Trump-era trade order. *Policy Circle*. https://www.policycircle.org/opinion/india-us-trade-in-services/
20. Chakradhar, J., & Choudhury, R. N. (7 Jul 2025). How policy uncertainty is rewriting Asia's economic future. *Madras Courier*. https://madrascourier.com/opinion/how-policy-uncertainty-is-rewriting-asias-economic-future/
21. Chakradhar, J. (5 Aug 2025). Trump, tariffs & trade wars. *Madras Courier*. https:

//madrascourier.com/opinion/trump-tariffs-trade-wars/

22. Chakradhar, J., & Bairwa, A. K. (12 Aug 2025). Who pays the cost of Trump's India tariff? *Telangana Today*. https://telanganatoday.com/opinion-who-pays-the-cost-of-trumps-india-tariff
23. Chakradhar, J., & Bairwa, A. K. (14 Aug 2025). Tariff turmoil: how a hike on Indian imports could shift U.S. consumer habits. *Madras Courier*. https://madrascourier.com/opinion/tariff-turmoil-how-a-hike-on-indian-imports-could-shift-u-s-consumer-habits/
24. Jadhav, P., & Chakradhar, J. (17 Aug 2025). Trump tariffs mark revival of 18th-century mercantilism. *Policy Circle*. https://www.policycircle.org/opinion/trump-tariffs-india-us-trade-2/
25. Chakradhar, J., & Gupta, R. (27 Aug 2025). India's agriculture sector struggles amid WTO paralysis, tariff hikes. *Policy Circle*. https://www.policycircle.org/opinion/agriculture-sector-wto-tariff-hurdles/
26. Chakradhar, J., & Gupta, R. (28 Aug 2025). WTO@30: trade, tariffs & lessons from India's agrarian struggles. *The Secretariat*. https://thesecretariat.in/article/wto-at-30-trade-tariffs-and-lessons-from-india-s-agrarian-struggles
27. Chakradhar, J., & Mishra, K. (3 Sep 2025). The 1/3 problem in India's poverty estimation. *Deccan Herald*. https://www.deccanherald.com/opinion/the-1-3-problem-in-india-s-poverty-estimation-3709237
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2. Orientation Programme for Research Scholars and Faculty Members in Social Sciences. GIDS (Giri Institute of Development Studies), Lucknow, India. May 23–26, 2016.
3. RIS Summer School on International Trade Theory and Practices. Research and Information System for Developing Countries (RIS), New Delhi. June 6–10, 2016.
4. 10th South Asian Training Program on CGE (Computable General Equilibrium) Modelling. Organized by SANEM (Dhaka), SAWTEE (Kathmandu), and CWS (New Delhi). Cox's Bazar, Bangladesh. August 12–16, 2017.
5. EXIM Bank and RIS Summer School on International Trade Theory and Practices. New Delhi. July 19–24, 2017.
6. Regional Conclave on ASEAN@50 and India–ASEAN Relations. NIAS, Bengaluru, India. December 7–8, 2017.
7. Workshop on Contemporary Rural Issues in India. Economic Analysis Unit, ISI Bangalore. March 27, 2018.
8. Capacity Building Workshop on Non-Tariff Measures: Economic Assessment and Policy Options. UNCTAD/ESCAP-ARTNet, Bangkok, Thailand. July 3–6, 2018.
9. Regional Workshop on Evidence-Based Trade Policy Making for Sustainable Development. Bangkok, Thailand. November 27–30, 2018.
10. ESCAP-ARTNeT Short Course on Trade Analysis Using R Studio. Bangkok, Thailand. November 29–30, 2018.
11. UNESCAP/ISO/UNCTAD Workshop on Non-Tariff Measures and International Standards

for Sustainable Development. Bangkok, Thailand. March 13–14, 2019.

12. 2nd IGC Patna Summer School in Development Economics. Organized by LSE, University of Oxford, CDS Thiruvananthapuram, and IIM Shillong. Patna, India. August 9–14, 2020.
13. Online Workshop on Panel Data Analysis. Department of Humanities, Delhi Technological University, New Delhi, India. August 17–22, 2020.
14. Virtual Workshop on Input–Output Analyses. CAREC Institute and ADB, Beijing, China. April 4–8, 2022.
15. UNCTAD YSI Summer School on Globalization and Development Strategies. Virtual. August 1–5, 2022.
16. Virtual Workshop on General Equilibrium Analysis with the Gravity Model: Theory and Applications. School of Economics, LeBow College of Business, Drexel University (Philadelphia, USA). November 28–December 2, 2022.

Best Paper Awards

1. Jadhav Chakradhar & Ritika Gupta. "Corporate Social Responsibility and Firm Financial Performance: A Moderating Effect of Economic Policy Uncertainty." Presented at the *First Virtual International Conference on Sustainable Finance, Economics, and Accounting in the Pre- and Post-Pandemic Era*, July 30–31, 2021. **[Best Paper Award – ICMAI, Financial Management]**. Link
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Achievements

1. Awarded a mini-grant of USD $1,200 by *UNESCAP, Bangkok* for a project on assessing fishing vessel capacity, subsidies, and non-tariff measures in relation to Sustainable Development Goals (September 2017 – January 2018).
2. Qualified the *State Eligibility Test (APSET)* in Economics for Assistant Professor and Lectureship, July 2013.
3. Awarded the *ICSSR Doctoral Research Fellowship* to pursue a Ph.D. in Economics at the Institute for Social and Economic Change (ISEC), Bengaluru.
4. Qualified the *UGC National Eligibility Test (NET)* in Economics, December 2013.
5. Received a travel grant of USD $1,000 to attend the 13th BMEB International Conference, organized in collaboration with the *Asian Development Bank (ADB)* and the *Asia-Pacific Applied Economics Association (APAEA)*, held in Bali, Indonesia, on August 29–30, 2019.

Reviewer Experience

Reviewer for: *Singapore Economic Review*, *FIIB Business Review*, *Emerging Markets Finance and Trade*, *Millennial Asia*, *Humanities and Social Sciences Communications*, *Economics and Business Review*, *International Journal of Applied Management Science*, *International Journal of Monetary Economics and Finance*, *International Journal of Corporate Governance*, *Global Business and Economics Review*, and *Journal of the Asia Pacific Economy*.

Membership in Professional Bodies

1. Indian Agricultural Economics Association
2. Telangana Economic Association (TEA)
3. The Indian Econometric Society (TIES)
4. Young Scholars Initiative (YSI), India Working Group

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I hereby declare that all the statements made in this Curriculum Vitae are accurate to the best of my knowledge.

Place: Hyderabad, India

Yours faithfully

(Jadhav Chakradhar)

Statement of Motivation and Current Research Interests

My research interests lie broadly in development economics, with a particular focus on poverty and inequality, education, labour markets, gender, and the socioeconomic factors that shape human development in developing countries. I am especially interested in understanding how disadvantages accumulate over the life course and how social, economic, and institutional environments influence individual opportunities and outcomes.

My current research examines the relationship between childhood multidimensional deprivation and educational outcomes in India. In my paper, *"Child Deprivation and Early Educational Outcomes: Evidence from India,"* I use longitudinal data from the Younger Cohort of the Young Lives study to examine how deprivation experienced during early childhood affects school enrollment and subsequent learning outcomes. I construct a child-specific multidimensional deprivation index covering health, education, and standard of living, using an adapted Alkire–Foster framework. The longitudinal nature of the Young Lives data allows me to connect conditions experienced during early childhood with later educational outcomes, providing an opportunity to examine processes of disadvantage over time.

An important component of my research is understanding why the effects of deprivation differ across social groups. My current analysis examines heterogeneity by gender, rural–urban location, caste, religion, and region. The findings suggest that multidimensional deprivation has particularly strong consequences for girls and children from socially disadvantaged communities, highlighting the importance of social structures and unequal access to resources in shaping educational trajectories.

I am interested in attending the NBER Workshop on Development Economics and Networks for Early-Career Researchers because I see an important opportunity to connect my existing research on deprivation and inequality with the emerging literature on social and economic networks. I would like to understand how family networks, peer effects, community relationships, information networks, and social interactions influence the transmission of opportunities and disadvantages. These mechanisms could provide a useful extension to my current research, which primarily focuses on the accumulation of multidimensional deprivation and its consequences for children's educational development.

The workshop would also allow me to learn from researchers working at the frontier of development economics and networks, receive feedback on my current research, and develop new empirical approaches for analysing social interactions using longitudinal data. I hope to use these insights to strengthen my current research agenda and develop future work examining how networks and social structures influence poverty, education, labour-market outcomes, and inequality in developing-country contexts.

I believe that participation in the workshop would therefore be valuable not only for developing my current research but also for shaping a broader research agenda at the intersection of development, inequality, human capital, and networks.

Dr. Jadhav Chakradhar

Child Deprivation and Early Educational Outcomes: Evidence from India

Abstract

This paper investigates the impact of child multidimensional deprivation on school enrollment and subsequent learning outcomes in Andhra Pradesh, India. Using longitudinal data from the Younger Cohort of the Young Lives study across three survey rounds (2002, 2006, and 2009–10), we construct a continuous multidimensional deprivation index along the dimensions of health, education, and standard of living, following the Alkire–Foster framework adapted to child-specific conditions. We employ rare-event logit models to examine the effect of deprivation on school enrollment and apply Instrumental Variable and Control Function approaches to identify causal impacts on learning outcomes. We find that children deprived across multiple dimensions—whether measured strictly or flexibly—are systematically less likely to attend formal schooling. We find that multidimensional deprivation significantly reduces school attendance across all social groups, with particularly strong effects among Muslims and backward castes, while intersectional analysis shows that Muslim girls experience the steepest attendance penalty. We find that multidimensional deprivation exerts large and statistically significant negative effects on children's learning outcomes. The effects are strongest for language and numeracy domains and remain robust under both strict and flexible deprivation definitions. Heterogeneity analysis further reveals that girls, Muslim children, and Scheduled Tribes experience the steepest learning penalties.

JEL Codes: I32 , I24 , I25, O15 , C21

Keywords: Multidimensional Deprivation; Educational Inequality; Learning Outcomes; Young Lives; India; Instrumental Variables; Causal Analysis

"The differences in child rearing that I observed are neither random nor trivial.
They are systematic and patterned, and they reflect the influence of social class."

— Unequal Childhoods: Class, Race, & Family Life, (Lareau, 2018)

1. INTRODUCTION

The interrelationship between poverty and educational attainment is a well-documented phenomenon in sociological and economic literature (Engle & Black, 2008; Ferguson, Bovaird, & Mueller, 2007; Glewwe, Hanushek, Humpage, & Ravina, 2011). While education is often legally guaranteed as a right, poverty systematically undermines both access and outcomes. The mechanism is twofold: first, poverty creates barriers to enrollment even in public systems through indirect costs and opportunity costs. Second, and more insidiously, it negatively impacts outcomes for those who are enrolled. Since education is a primary driver of individual productivity and future earnings, this dynamic creates a vicious cycle (Myrdal, 1944; Myint, 1965) where poverty curtails educational opportunities, which in turn perpetuates poverty across generations (Philip, 1958; Rosenberg, 1960). In countries like India, the notion of education as an *equalizer* is significantly contested (Blaug, 1976). This study, therefore, focuses on the hindrances that deprivation and poverty pose to educational attainment and outcomes.

In the case of children, however, the notion of poverty extends beyond monetary deprivation to encompass a multidimensional construct that captures deficits in health, nutrition, and home environment—dimensions that monetary measures alone fail to reflect (Mohanty, 2011; Kim, 2019; Belete, 2022). It is widely recognized that children born into poorer households are more likely to experience limited educational opportunities and to replicate the socioeconomic disadvantages of their parents, perpetuating cycles of deprivation across generations (Li, Yin, & Jiang, 2020; Ballón, Cockburn, Dessy, & Diarra, 2018; Shay, Shavit, & Sasson, 2024). The impact of poverty on child development is profoundly complicated by the intersection of social identities such as religion, caste, and gender, which shape access to household resources and subsequent educational outcomes in India (Borooah & Iyer, 2005). While existing literature robustly establishes the intergenerational transmission of poverty (Dutta, 2021; Kim, 2019; Ge & Wang, 2019), the precise mechanisms facilitating this transmission remain less explored. This study moves beyond documenting deprivation as a final outcome to instead conceptualize early-life multidimensional deprivation as a critical mechanism of reproduction. We specifically investigate how this deprivation impacts two pivotal educational transitions: initial school enrollment and subsequent learning outcomes in math, language, and other subjects. We explore the interaction be- tween group identity (caste and religion) and multidimensional deprivation, testing how this interaction differentially predicts both school enrollment and learning achievements.

We propose this question in the context of two Indian states—Andhra Pradesh and Telangana—for which we use data from the Younger Cohort of the Young Lives study up to Round 3. India was selected as one of the four Young Lives countries because it represents a lower-middle-income setting with substantial regional heterogeneity in poverty and human development indicators (Galab et al., 2014). Within India, Andhra Pradesh was chosen for its pioneering poverty-reduction initiatives, administrative capacity, and socio-economic diversity across agro-climatic regions (Barnett, Galab, Pankhurst, Woldehanna, & Porter, 2017)[1] The Young Lives design deliberately sampled rural and urban sentinel sites, oversampling poorer districts to ensure adequate representation of low-income households and to enable longitudinal tracking of child development outcomes over time (Barnett et al., 2017).

We first utilize the detailed panel information on children captured by the Young Lives (YL) study across Rounds 1, 2, and 3 to construct a continuous deprivation index that measures multidimensional deprivation along the dimensions of health, education, and standard of living, following the UNDP Multidimensional Poverty Index (MPI) framework (Alkire & Santos, 2011; UNDP, 2010). However, given the richness of the Young Lives data, we modify and refine this framework by replacing several of the original indicators within the health and education dimensions and by adding additional indicators to the standard of living dimension to make the index more representative of child-specific deprivation. We further construct two distinct deprivation indices—a *strict* and a *flexible* version—by defining parental educational deprivation at the levels of literacy and matriculation, respectively. These indices allow us to capture variations in the severity and breadth of multidimensional deprivation among children. We employ the deprivation index to estimate the impact of multidimensional poverty on education (Mohanty, 2011; Dutta, 2021). Specifically, we use a modified binary dependent variable model suitable for rare events[2] to examine the impact of deprivation on initial school enrollment. We further estimate the effect of multidimensional deprivation on educational outcomes—measured through Mathematics, PPVT, and EGRA scores—using Instrumental Variable (IV) regression and Control Function (CF) approaches to address potential endogeneity and measurement bias.

We uncover several interesting findings. Household's decisions to make children enter and remain in school are not shaped solely by household income but by overlapping deprivations in health, nutrition, parental education, and living conditions that jointly influence their readiness and ability to participate in formal education. In contexts such as India, these disadvantages often accumulate from early childhood,

[1] Following the bifurcation of Andhra Pradesh in 2014, the Young Lives sample was extended to include Telangana, thereby capturing intra-regional variation in economic growth, social policy, and educational outcomes. However, this paper uses data till the 2009–10 survey round, when the study area constituted a single undivided state of Andhra Pradesh.

[2] With the aim of identifying the effect of deprivation on the probability of school enrollment at the expected age of entry.

reinforcing cycles of exclusion where deprivation simultaneously limits both the demand for and access to schooling. While monetary poverty has long been recognized as a barrier to education, multidimensional deprivation provides a more comprehensive lens by capturing the structural constraints—such as parental illiteracy, poor health infrastructure, and inadequate home environments—that hinder school participation. By quantifying the impact of multidimensional deprivation on enrollment, this analysis aims to reveal the extent to which early disadvantage translates into unequal educational access and to highlight the enduring mechanisms through which deprivation shapes children's life trajectories.

Understanding how multidimensional deprivation influences children's learning trajectories is central to the broader discourse on educational inequality in developing contexts. Early-life deprivation is rarely confined to a single dimension—it spans deficits in health, nutrition, parental education, and household living conditions that cumulatively shape children's cognitive and non-cognitive development. In low- and middle-income settings such as India, these overlapping disadvantages manifest not only in delayed school entry but also in persistent learning gaps that widen with age. While previous research has documented the general association between poverty and education, the specific mechanisms through which multidimensional deprivation affects learning outcomes remain underexplored, particularly within a causal framework. This study addresses this gap by empirically assessing how composite deprivation during early childhood translates into disparities in cognitive, language, and numeracy performance over time. By leveraging a unique longitudinal dataset that tracks children from early to middle childhood, we estimate the magnitude and persistence of deprivation's effects across multiple learning domains. The inclusion of both strict and flexible deprivation measures allows for a nuanced understanding of how varying intensities of disadvantage influence educational performance. In doing so, the analysis provides new evidence on the enduring impact of structural inequalities in early life, underscoring the need for integrated policy interventions that target health, education, and household well-being simultaneously to promote equitable learning outcomes.

Beyond estimating the average impact of childhood multidimensional deprivation, this study also examines how these effects vary across social, spatial, and demographic groups. The heterogeneity analysis reveals that the burden of deprivation is far from uniform: its adverse impact on learning outcomes is markedly stronger among girls, rural children, and those belonging to socioeconomically marginalized communities. Regional disparities between Andhra Pradesh and Telangana persist, reflecting uneven institutional development and public investment in early education. Similarly, children from Muslim and Scheduled Tribe households experience substantially larger learning penalties, underscoring the intersection of structural deprivation with entrenched social exclusion. By

documenting these differentiated effects, the study highlights that multidimensional deprivation does not simply lower average learning achievement—it amplifies existing social hierarchies and spatial inequalities, shaping divergent educational trajectories from early childhood. This emphasis on heterogeneity underscores the need for policy responses that are both equity-sensitive and context-specific, targeting those groups most vulnerable to the compounding effects of deprivation.

The remainder of the paper is organized as follows. Section 2 reviews the existing literature , Section 3 provides contextual background through the Andhra Pradesh story of child education, Section 4 outlines the econometric framework. Section 5 presents the descriptive and summary statistics. Section 6.1 and Section 6.2 report the main empirical findings on educational enrollment and learning outcomes, respectively. Section 6.2.1 explores heterogeneity in the effects across gender, caste, religion, and region. Section 7 discusses key policy implications.

2. LITERATURE REVIEW

The study of poverty and child well-being has evolved substantially from its early focus on monetary income deprivation toward multidimensional frameworks that better capture the range of deprivations children face. Early conceptual advances, drawing on Sen's capability approach (Sen, 1992, 1999a, 1999b), emphasized that poverty cannot be understood purely as a lack of income but must account for deficiencies in health, education, nutrition, and living standards that constrain human capabilities. Recent literature extends this understanding to the specific context of children, recognizing that child poverty has distinct characteristics and consequences because of children's developmental vulnerabilities and dependency on household resources and institutions (Mohanty, 2011; Kim, 2019; Garc´ıa & Rit-terbusch, 2015). A growing consensus has emerged that multidimensional poverty, rather than income poverty alone, provides a more complete picture of child disadvantage and its long-term educational and developmental implications (Biggeri & Ferrone, 2021; Clausen, Barrantes, Trivelli, & Salas, 2025).

A substantial body of empirical work underscores the persistence of multidimensional child poverty and its heterogeneous nature across regions and socioeconomic groups. In the Indian context, multi- dimensional poverty indices (MPIs) have been widely applied to measure overlapping deprivations in health, education, and living standards (Dehury & Mohanty, 2015; Mohanty, 2011). Using data from the National Family Health Survey (NFHS), Mohanty (2011) demonstrated that multidimensionally poor households face significantly higher infant and under-five mortality rates, underscoring how interlinked deprivations in education, health, and wealth manifest in adverse child survival outcomes. Similarly, Das and Mohanty (2024) found that multidimensionally poor individuals in India exhibit a life expectancy four years lower than their non-poor counterparts, with pronounced rural–urban gaps. These findings

collectively reinforce the argument that multidimensional deprivation captures more meaningful welfare differentials than income alone, with direct implications for child education and development.

Empirical studies in South Asia and other developing regions have further shown that multidimensional child poverty directly influences both school enrollment and learning outcomes. In India and Bangladesh, Dutta (2021) employed Demographic and Health Survey data and a logistic framework to estimate the probability of child deprivation. The study found that children in multidimensionally poor households are substantially less likely to attend school or progress through grades, and that maternal education and empowerment mitigate these risks. Similarly, in China, Ge and Wang (2019) documented that multidimensional poverty significantly reduces children's academic achievement in rural areas, with social relationships mediating the effects of poverty on learning. These results echo evidence from Central America, where multidimensional deprivation, shaped by parental education, rural residence, and ethnicity, constrains early childhood development and future educational participation (Guille´n-Ferna´ndez, 2024). Across contexts, the common thread is clear: multidimensional poverty limits both access to and quality of educational experiences.

Several studies also emphasize that multidimensional deprivation is distinct from monetary poverty, both conceptually and empirically. Ballo´n et al. (2018) and Singh and Sarkar (2015b) show that many children who are not monetarily poor still experience significant non-income deprivations in schooling, housing, and health. This mismatch implies that income-based poverty measures underestimate educational disadvantage, as children may face barriers to learning stemming from health, environmental, or social deficits even in relatively wealthier households. Kim (2019) reinforces this argument by showing that in Ethiopia, India, Peru, and Vietnam, children escaping income poverty often remain multidimensionally deprived, suggesting persistent structural and intergenerational disadvantages. Likewise, Belete (2022) found that a considerable proportion of non-monetarily poor children in Ethiopia remain deprived in nutrition and health, indicating that education-related poverty alleviation policies must ad- dress overlapping non-income deficits.

In addition to cross-sectional evidence, longitudinal studies have revealed that early-life deprivation exerts lasting effects on later educational outcomes. Using census-linked data, Shay et al. (2024) demonstrated that children born into the lowest income quintiles perform significantly worse on standardized tests in primary school, even after controlling for later family income. The study underscores that early childhood poverty—particularly during the first two years of life—has a persistent, causal impact on cognitive and learning trajectories. Similar conclusions emerge from work by Kazakova, Leturcq, and Panico (2024), who constructed longitudinal multidimensional deprivation indicators for early childhood in France, finding that deprivation in material and parenting dimensions during the first

five years has long-term educational consequences. These results collectively highlight that the timing and depth of deprivation, rather than its monetary measure alone, determine its cumulative impact on child learning and school participation.

In the Indian case, multidimensional deprivation is closely tied to regional and gender disparities in school enrollment. Studies using the Indian Human Development Survey have shown that deprivation in education and living conditions remains regionally clustered, with northern and eastern states exhibiting higher deprivation scores and lower school participation rates (Dehury & Mohanty, 2015). The intersection of poverty, gender, and geography thus emerges as a critical determinant of both access and outcomes. For instance, Diwakar (2023) analyzed the effects of violent conflict and poverty in India and found that conflict amplifies the negative effects of poverty on literacy and numeracy, particularly for girls. These findings illustrate that poverty interacts with broader social and structural conditions—such as safety, gender norms, and local governance—to influence children's educational trajectories.

Cross-country comparative studies deepen this understanding. Evidence from China suggests that despite major reductions in extreme monetary poverty, child deprivation remains persistent and even widening in some functional domains. Lin and Chen (2025) found that while capability deprivation has declined, functionings deprivation—particularly related to education and social inclusion—has increased, emphasizing that income growth alone does not ensure improvements in child well-being. In Malawi, Chatata and Chirwa (2025) employed propensity score matching to estimate the causal effect of multidimensional poverty on antenatal care utilization, illustrating how non-income deprivation restricts access to basic health services. Although focusing on maternal care, this study's methodological approach and findings are relevant to child education, as similar mechanisms—information, accessibility, and awareness—shape educational participation among the poor.

Beyond correlational analyses, the literature increasingly employs quasi-experimental and instrumental variable methods to uncover causal links between deprivation and educational outcomes. Serneels and Dercon (n.d.) used an instrumental variable approach to identify the causal effect of maternal aspirations on children's schooling in India, finding that higher aspirations, conditional on income and community factors, substantially improve enrollment and progression. Likewise, Gennetian, Bos, and Morris (n.d.) demonstrated how instrumental variable analysis can be used to explore mediating channels between policy interventions and behavioral outcomes, providing a methodological framework for causal inference in social experiments. Randomized and quasi-experimental studies outside India provide complementary insights. Glewwe et al. (2011) reviewed nearly two decades of experimental and quasi-experimental evidence and found that most school resource inputs have limited effects on learning outcomes once teacher and institutional quality are accounted for. However, targeted interventions—such

as teacher incentives, technology-assisted instruction, and remedial tutoring—have demonstrated substantial gains in learning.

Evidence from the broader development economics literature reinforces these conclusions. Duflo (2001) documented significant long-term gains in wages and schooling attainment from Indonesia's large-scale school construction program, one of the earliest credible quasi-experimental demonstrations of education's causal returns. Similarly, Muralidharan and Sundararaman (2011) showed through randomized evaluations in India that teacher incentive programs significantly raised student test scores, particularly in mathematics. More recently, Banerjee et al. (2017) synthesized evidence from over 200 randomized controlled trials to conclude that pedagogical innovations and targeted remedial programs yield some of the largest cost-effective improvements in learning outcomes among disadvantaged children. These findings underscore that well-designed interventions can mitigate the adverse effects of multidimensional deprivation by enhancing educational quality and engagement. In this vein, Henkel, Horne-Robinson, Kozhakhmetova, and Lee (2024) provided contemporary experimental evidence from Ghana showing that low-cost AI-based tutoring can generate large improvements in math learning, suggesting scalable technological pathways for addressing learning gaps in resource-constrained settings. Thus multidimensional poverty has profound and enduring impacts on both school participation and learning outcomes, operating through multiple inter- linked deprivations. While income growth and traditional poverty reduction are necessary, they are in- sufficient to ensure equitable educational progress. Deprivations in parental education, nutrition, health, infrastructure, and information access often persist even among non-poor households, contributing to persistent educational inequalities. Interventions that target specific dimensions of deprivation—such as quality teaching, parental support, and technological inclusion—show promise in disrupting these pat- terns. Yet, as noted by Mohanty (2011) and Biggeri and Ferrone (2021), few studies directly integrate a multidimensional deprivation framework with educational outcomes in a unified analytical model.

The current study contributes to this gap by empirically assessing how multidimensional deprivation affects both enrollment and learning outcomes among children in India, using causal estimation strategies to identify these effects. By doing so, it aligns with the growing body of literature that calls for child-centered, multidimensional approaches to poverty research and educational policy, aiming to inform interventions that can simultaneously address the interlocking disadvantages constraining children's development.

2.1. The Andhra Pradesh Story of Child Education

Andhra Pradesh and Telangana offer a compelling regional case for examining the links between

multidimensional deprivation and child education. Historically, these states have shown considerable variation in both access to schooling and the pace of educational progress, reflecting broader disparities across India's southern and eastern regions. As shown in Figure 1, annual enrollment growth rates at both primary and upper-primary levels have fluctuated over time, yet structural gaps have persisted. The expansion of schools and improvements in overall literacy have not entirely translated into uniform progress. Female literacy, while steadily improving, continues to trail behind male literacy, and the differential between primary and upper-primary enrollment growth remains substantial. Figure 2 further contextualizes these trends by illustrating the broader socioeconomic environment of Andhra Pradesh. While the state has experienced robust economic growth—reflected in increasing GSDP and per capita income—progress in basic child health outcomes such as immunization has been uneven. Despite overall improvements, disparities persist across districts and population subgroups, indicating that economic advancement alone has not eradicated the multifaceted deprivations affecting children's welfare.

The foundational deprivation experienced by children in the state is both widespread and multidimensional. Studies consistently show that even among the least poor households, a substantial majority of children experience overlapping deprivations in education, health, and nutrition (Singh & Sarkar, 2014). These disadvantages are not static: idiosyncratic household shocks such as paternal illness or livestock loss reduce educational investments and impair cognitive outcomes (Dhanaraj, Paul, & Gade, 2019). Economic pressures further push children into the labour force, with agricultural work—particularly cottonseed pollination—competing directly with schooling time and disproportionately affecting girls' educational participation (Morrow & Vennam, 2010). Even early educational interventions appear insufficient to offset these structural constraints; participation in early childhood education programs shows negligible effects on later test performance, indicating that the quality and consistency of provision remain problematic (Alwani, 2019).

A critical trend shaping the state's educational landscape is the rapid expansion of a heterogeneous school market, driven by the rise of low-fee private (LFP) schools. Between 2002 and 2009, private school enrolment among eight-year-olds nearly doubled, yet access remained skewed against rural populations, poorer households, and girls (Woodhead, Frost, & James, 2013; Galab, Kumar, Reddy, Singh, & Vennam, 2011). This diversification has created a dynamic and often stressful decision environment for families, who increasingly engage in successive school switches as they navigate perceived hierarchies of quality (James & Woodhead, 2014). However, the core promise of private schooling—superior learning outcomes—has not been substantiated by rigorous evidence. A large-scale longitudinal randomized controlled trial in Andhra Pradesh found that private schools added no measurable value to children's learning compared to government schools, with scholarship recipients showing no significant

improvement even after five years of private education (Karopady, 2014).

3. Data & Econometric Framework

3.1. Data & Variables

The empirical analysis of this paper draws on the longitudinal Young Lives dataset from India, which follows a cohort of children from early childhood through adolescence across three survey rounds (Round 1: 2002, Round 2: 2006, and Round 3: 2009–10). Specifically, the younger cohort of the Young Lives data provides a rich panel structure capturing a wide range of individual-, household-, and community-level characteristics that vary both over time and across children. In addition to a set of time-invariant child and household attributes, the data track several time-varying indicators that allow us to construct multidimensional measures of childhood deprivation. The deprivation score is computed using information from all three rounds, combining both static and dynamic components of the child's living conditions, the details of which are discussed in the online supplementary material. The estimation framework of the paper consists of three components. The first, presented in the Appendix, relates to the construction of the multidimensional deprivation index. The second and main part examines the impact of early-life deprivation on educational enrollment outcomes, where the dependent variable indicates whether the child attended formal schooling. This analysis exploits the panel dimension of the data, using information on school attendance primarily from Rounds 2 and 3. To ensure robustness, we estimate both a standard logit specification and a random-effects panel probit model. Finally, the third estimation focuses on educational outcomes in terms of learning performance, measured using the Peabody Picture Vocabulary Test (PPVT) and other standardized assessments available only in Round 3, which captures the child's cognitive achievement around the age of eight.

Table 1 presents the complete list and categorization of variables used in the empirical analysis. The study employs two primary sets of dependent variables corresponding to the two main outcome dimensions: school participation and learning performance. Formal school attendance, a binary indicator denoting whether the child has ever enrolled in a formal school, captures the child's participation outcome, while cognitive and academic achievements are assessed using multiple standardized learning measures such as the Peabody Picture Vocabulary Test (PPVT), Mathematics Achievement Score, Early Grade Reading Assessment (EGRA), and Cognitive Development Assessment (CDA). These Rasch-standardized scores collectively represent different dimensions of cognitive and linguistic development during early schooling years. The core explanatory variables are the multidimensional deprivation in-

dices—constructed under both strict and flexible definitions—which serve as the key measures of early-life deprivation. A comprehensive set of control variables accounts for demographic, socioeconomic, and geographic heterogeneity, including gender, sector of residence, religion, caste, and regional affiliation. Additionally, parental education levels (mother's and father's years of schooling) and the child's birth weight are employed as instrumental variables, reflecting pre-determined household and biological characteristics that influence educational outcomes through their effect on early deprivation but not directly on the child's current learning scores.

3.2. Rationale for Causal Analysis and Data Relevance

It is well-recognized that children experiencing higher levels of multidimensional deprivation are more likely to delay or forego entry into formal schooling (Malik, 2013; Singh & Sarkar, 2015a). This relationship is conceptually intuitive and empirically observed in multiple contexts. However, acknowledging this direction of association does not substitute for an understanding of its magnitude, shape, or heterogeneity. Quantifying the causal impact of deprivation on educational enrollment and learning outcomes remains essential for at least three reasons. First, policymakers require precise estimates of the magnitude of the effect to effectively design and target early interventions. Second, establishing the functional relationship helps identify thresholds beyond which the probability of timely school entry or learning attainment sharply declines. Third, causal estimation techniques such as the control function approach allow researchers to move beyond descriptive associations and correct for endogeneity and selection bias that often confound this relationship.

Although the Young Lives data used in this study are temporally dated and geographically restricted to Andhra Pradesh and Telangana, the mechanisms through which early-life deprivation shapes educational outcomes are structural and deeply persistent. Figure 1 demonstrates that disparities in enrollment and literacy have remained remarkably stable over nearly two decades, while Figure 2 reveals that improvements in health and economic growth have not fully translated into educational convergence. These enduring patterns imply that the developmental processes captured by earlier rounds of the Young Lives data continue to inform the present educational landscape.

Moreover, the panel nature of the Young Lives survey provides an analytical advantage unparalleled by any other Indian dataset. Its longitudinal structure allows for tracing how early-life deprivations in health, nutrition, and household conditions accumulate and manifest in later educational outcomes. No other national data source offers comparable depth in child-level tracking across time. Thus, while the data are regionally constrained, they allow for causal inference on mechanisms that remain highly relevant in contemporary India. Many early childhood programs—such as Anganwadi services

(Debata, Ranganath, & TS, 2023), the Mid-Day Meal scheme (Chakraborty & Jayaraman, 2019), and foundational literacy initiatives—have remained structurally consistent, underscoring that the pathways linking deprivation and education have not fundamentally changed. Consequently, the results derived here provide not only a historical lens but also a rigorous and enduring benchmark for understanding the deprivation–education gradient that continues to shape educational inequality in India.

4. ECONOMETRIC FRAMEWORK

This paper employs a multi-stage econometric framework to first construct a measure of childhood multidimensional deprivation (CMD) and then estimate its causal impact on early-life educational attainment. The analysis proceeds in three sequential steps: (1) the definition and measurement of multi-dimensional deprivation, (2) the analysis of the incidence of severe deprivation as a rare event, and (3) the estimation of the effect of this deprivation on subsequent learning outcomes.

4.1. Measurement of Child Multidimensional Deprivation (CMD)

Let i = 1, . . . , N index children in the sample. We use UNDP (2010) method with dimension level modification to adapt to multidimensional deprivation condition at the early childhood level i.e. 1-8 years. We conceptualize multidimensional deprivation across D distinct dimensions (e.g., health, education, living standards). Each dimension d is itself composed of K_d specific indicators. The deprivation status of child *i* in indicator *k* of dimension *d* is determined by comparing their achievement, a_i^{dk}, to a normative deprivation threshold, τ_{dk}. This is formalized by the indicator function:

$$\boldsymbol{g_i^{dk} = I\left(a_i^{dk} < \tau^{dk}\right)}$$

which equals 1 if the child is deprived and 0 otherwise.

The deprivation score for each dimension is a weighted sum of its indicators. Let wd be the weight assigned to dimension *d*, and w_{dk} be the weight assigned to indicator *k* within dimension *d*, with the weights satisfying $\sum_{d=1}^{D} w_d = 1$ and $\sum_{k=1}^{K_d} w_{dk} = 1$ for all *d*. The child's overall deprivation score, CMD_i , is then constructed as:

$$\mathbf{CMD_i} = \sum_{\mathbf{d=1}}^{\mathbf{D}} \mathbf{w_d} \left(\sum_{\mathbf{k=1}}^{\mathbf{K_d}} \mathbf{w_{dk}}\ \mathbf{g_i^{dk}} \right)$$

This continuous score, bounded between 0 and 1, reflects the breadth and depth of a child's deprivations. For certain analyses, this continuous measure is dichotomized to identify a state of severe deprivation. The detailed identification of CMD and estimation using Suppa (2023) is given in the Online Appendix.

4.2. Estimating the Association Between Deprivation and Educational Attainment

Our fundamental relationship of interest is specified as a linear probability model for ease of interpretation, with key results verified using non-linear models:

$$\textbf{Formal School}_{it} = \boldsymbol{\alpha} + \boldsymbol{\beta} \cdot \textbf{Deprivation}_{it} + \boldsymbol{X}'_{it}\boldsymbol{\gamma} + \boldsymbol{\epsilon}_{it}$$

where $FormalSchool_{it}$ is a binary indicator for child i's school attendance in round t, $Deprivation_{it}$ denotes the deprivation score (in its continuous or binary form), and $\boldsymbol{X}_{it}$ is a vector of control variables. The empirical analysis employs a rare events logistic regression to account for the substantial imbal- ance between children attending and not attending school. When the number of negative outcomes (non-attendance in this context) is very small, the standard maximum likelihood estimator can produce biased coefficient estimates and severely underestimate the probability of the rare event. The rare events logit (Firth (1993)'s penalized likelihood) corrects for this small-sample bias, providing more reliable and accurate estimates. We employ three distinct estimation methods to address different econometric concerns inherent in our data:

Firth Logistic Regression: To address the finite-sample bias and potential separation issues arising from the rare event nature of non-attendance, we estimate a penalized logistic regression. The penalized log-likelihood is given by:

$$\mathbf{l}^*(\boldsymbol{\theta}) = \mathbf{l}(\boldsymbol{\theta}) + \frac{\mathbf{1}}{\mathbf{2}}\mathbf{log}|\boldsymbol{I}(\boldsymbol{\theta})|$$

where $\ell(\theta)$ is the standard log-likelihood and $|I(\theta)|$ is the determinant of the Fisher information matrix (Firth, 1993).

Random Effects Probit: To account for unobserved, time-invariant child-level heterogeneity (αi), we estimate a random effects probit model:

$$P(\text{FormalSchool}_{it} = 1) = \Phi(\alpha_i + \beta\text{Deprivation}_{it} + X'_{it}\gamma), \quad \alpha_i \sim N(0, \sigma_\alpha^2)$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function.

Linear Probability Model with Cluster-Robust Standard Errors: For a more interpretable coefficient and to relax the distributional assumptions of non-linear models, we estimate a linear probability model. We cluster standard errors at the child level to account for arbitrary within-individual correlation across survey rounds:

$$\widehat{\boldsymbol{V}_{\boldsymbol{Cluster}}} = (\boldsymbol{X}'\boldsymbol{X})^{-1}\left(\sum_{\boldsymbol{i}=\boldsymbol{1}}^{\boldsymbol{N}} \boldsymbol{X}_{\boldsymbol{i}}'\widehat{\boldsymbol{\epsilon}_{\boldsymbol{i}}\boldsymbol{\epsilon}_{\boldsymbol{i}}'}\boldsymbol{X}_{\boldsymbol{i}}\right)(\boldsymbol{X}'\boldsymbol{X})^{-1}$$

To estimate the association between multidimensional deprivation and educational attainment, we employ a hierarchical control variable strategy. This approach allows us to examine the sensitivity of the deprivation coefficient βˆ to the inclusion of different sets of confounding factors, following best practices for establishing robust empirical relationships (Altonji, Elder, & Taber, 2005; Oster, 2019). The vector $\boldsymbol{X}_{it}$ is expanded sequentially across three specifications. The minimal specification includes fundamental demographic and economic controls: the child's age, gender, caste, and a household asset index. The main specification augments this by adding religion, geographic region (state/province), and sector (rural/urban), which capture broader socio-cultural and spatial disparities in educational access. Finally, the extended specification incorporates the highest parental education level, a key determinant of both childhood deprivation and educational investment (Behrman, Sengupta, & Todd, 1999).

The robustness of the core association is rigorously assessed through a multi-faceted stability test. A robust finding is one where the estimated coefficient $\hat{\beta}$ for deprivation remains statistically significant and economically stable across three key dimensions (Imbens, 2015). First, we assess its consistency across different estimation methods, namely the Linear Probability Model (LPM), Firth Logistic Re- gression, and Random Effects Probit. This ensures our results are not an artifact of a specific functional form or estimation technique. Second, we examine its stability across the hierarchically nested sets of control variables. A coefficient that is highly sensitive to the inclusion of additional controls would suggest a fragile association potentially confounded by omitted variables. Third, we verify that the re- lationship holds regardless of how deprivation is operationalized, using both the continuous deprivation score and a binary indicator for severe deprivation.

It is crucial to delineate the interpretation of our estimates. The coefficients derived from Equation 3 should be interpreted as conditional partial correlations that may not reflect a causal effect. A causal interpretation would require the strong and untestable assumption of conditional independence—that after controlling for the observed covariates $\boldsymbol{X}_{it}$, the deprivation measure is orthogonal to all other unobserved

determinants of school attendance, formally that $E[\epsilon_{it}|\text{Deprivation}_{it}, X_{it}] = 0$. While our extensive and hierarchically-included controls mitigate concerns related to observable confounding, and the stability of $\hat{\beta}$ provides some assurance against overt omitted variable bias, we cannot definitively rule out confounding from unobserved factors, such as innate child ability or parental aspirations (Manski, 1993; Gelbach, 2016).

Estimating the Impact of Deprivation on Learning Outcomes

Our analysis focuses on learning outcomes at age 7-8, measured across three cognitive domains: language ability (PPVT), mathematical achievement, and reading skills (EGRA). The baseline specification employs an Ordinary Least Squares framework to estimate the association between multidimensional deprivation and learning outcomes:

$$\boldsymbol{Y_i = \alpha + \beta \cdot \text{CMD}_i + \gamma' X_i + \varepsilon_i},$$

where Y_i represents the learning outcome for child i, CMD_i denotes the continuous childhood multi-dimensional deprivation score constructed in Equation 2, and $\boldsymbol{X}_i$ is a comprehensive vector of control variables including parental education, household assets, regional fixed effects, religious affiliation, sector of residence, caste categories, and gender. The parameter β captures the partial association between deprivation and learning outcomes, conditional on the observed covariates. However, the OLS estimator relies on the strong assumption that $E[\,\varepsilon_i \mid \text{CMD}_i, X_i\,] = 0$, which may be violated if deprivation is correlated with unobserved determinants of learning outcomes. Such correlation could arise from omitted variable bias, measurement error in the deprivation index, or reverse causality. To address these endogeneity concerns, we implement an instrumental variables (IV) approach using two-stage least squares (2SLS) estimation. The structural equation of interest remains:

$$\boldsymbol{Y_i = \alpha + \beta \cdot \text{CMD}_i + \gamma' X_i + \varepsilon_i}$$

but we now instrument the endogenous deprivation measure CMD_i with a set of exogenous instruments $\boldsymbol{Z}_i$ that satisfy the relevance condition $\text{Cov}(Z_i, \text{CMD}_i \mid X_i) \neq 0$ and the exclusion restriction $E[\,\varepsilon_i \mid Z_i, X_i\,] = 0$. The first-stage equation is specified as:

$$\mathbf{CMD}_i = \boldsymbol{\pi}_0 + \boldsymbol{\pi}' \boldsymbol{Z}_i + \boldsymbol{\phi}' \boldsymbol{X}_i + \boldsymbol{\nu}_i,$$

and the second-stage estimates the causal parameter β using the predicted values $\widehat{\mathrm{CMD}}_i$ from the first-stage regression. To complement this identification strategy, we employ the control function approach (Wooldridge, 2015), which provides consistent estimates under the same identifying assumptions while offering additional diagnostic power. This method involves estimating the first-stage equation (9) and including the residuals $\hat{v}_i$ as an additional regressor in the outcome equation:

$$\boldsymbol{Y}_i = \boldsymbol{\alpha} + \boldsymbol{\beta}\, \mathbf{CMD}_i + \boldsymbol{\lambda}\hat{\boldsymbol{v}}_i + \boldsymbol{\gamma}' \boldsymbol{X}_i + \boldsymbol{\varepsilon}_i$$

The control function approach provides a direct test for endogeneity through the statistical significance of λ , and it yields efficiency gains when the errors are jointly normally distributed. We use parental education—mother's and father's years of schooling—as excluded instruments, a practice well established in the economics of education literature[3].

5. Summary Results

Table 2 reports descriptive statistics for the key variables used in the analysis[4] . The mean deprivation score equals 0.220 under the strict definition and 0.194 under the flexible definition, indicating moder- ate levels of multidimensional deprivation among children in the sample. The relatively low standard deviations suggest that deprivation intensity is clustered around the mean, while the maximum value of approximately 0.46 indicates that even the most deprived children experience partial rather than extreme deprivation. For econometric analysis, both deprivation measures are standardized to have a mean of zero and unit variance, which facilitates interpretation of regression coefficients in terms of standard deviation changes and allows direct comparison across specifications. The average child in the sample is 4.67 years old, capturing the early childhood cohort that is central to the analysis. Gender composition is nearly balanced, with female children comprising about 47 percent of the sample. The caste distribution

[3] See Behrman and Rosenzweig (2002); Chevalier (2004); Carneiro, Meghir, and Parey (2013); Behrman, Sengupta, and Todd (2005); Glick and Sahn (2000).

[4] Table 1 provides detailed definitions and categorization of all variables used in the analysis.

reflects a larger representation of children from OBC and General categories, while approximately 7 percent of the sample belongs to the Muslim community. Geographically, about three-quarters of the sample resides in rural areas, and nearly 65 percent are from Telangana, providing substantial variation across socioeconomic and spatial contexts. Parental education levels are low on average, with fathers completing about 6.2 years and mothers 4.4 years of schooling, highlighting limited educational attainment within households. Finally, the asset index exhibits considerable dispersion, indicating substantial heterogeneity in household economic conditions. Table 3 presents average PPVT, Mathematics, and EGRA scores across key demographic groups. Clear disparities are visible across caste categories, with children from Scheduled Tribe households consistently recording lower mean scores across all three assessments, while children from Other caste groups exhibit the highest average performance. Gender differences are relatively modest, with boys scoring slightly higher in PPVT and mathematics, while girls perform marginally better in EGRA. Learning outcomes also vary by religion and sector, with Hindu children and those residing in urban areas displaying higher average scores compared to their counterparts. Overall, the patterns suggest systematic variation in early learning outcomes along social and spatial dimensions, motivating the multivariate analysis that follows.

6. RESULTS AND DISCUSSION

6.1. Deprivation on Educational Enrollment

The empirical analysis reveals a consistent and robust negative relationship between multidimensional deprivation and formal school attendance. As shown in Table 4, both strict and flexible deprivation measures exhibit statistically significant negative effects on school attendance across all model specifications and control sets. The coefficients remain highly significant at the 1% level in the Firth logit models and display remarkable stability across specifications. This consistency demonstrates that the negative association between deprivation and school attendance is not sensitive to estimation technique, choice of controls, or distributional assumptions. The negligible variation in coefficients across specifications provides strong evidence that the estimated deprivation effects are both genuine and precisely measured. As shown in Table 4, the coefficients remain virtually unchanged when moving from standard logit to Firth logit specifications, suggesting that the relationship is not driven by estimation bias or rare-event concerns. In the Indian context, Kumar and KB (2022) find that deprivations in child nutrition, maternal health, and financial inclusion substantially reduce school attendance across districts, while Baiju (2023) report that educational deprivation in India is driven largely by non-attendance in states with high multidimensional poverty.

Globally, the UNDP and OPHI (2024) and MPPN (2023) highlight that school attendance deprivation is among the most persistent components of education-related poverty, with over 259 million multidimensionally poor individuals worldwide simultaneously deprived in both schooling and nutrition. In terms of magnitude, the estimated effects are economically meaningful. Given the standardized construction of the deprivation index, a one standard deviation increase in childhood multidimensional deprivation is associated with a lower probability of attending formal school. This negative gradient persists across both strict and flexible measures, with the flexible index showing slightly greater variability but an equally strong adverse pattern. The robustness of these findings across logit and Firth logit frameworks further reinforces the credibility of the results.

The persistence and stability of deprivation effects across specifications indicate that interventions addressing multidimensional deprivation could yield substantial improvements in school participation. The similarity in results between strict and flexible deprivation measures implies that policymakers can rely on either index for targeting, though the flexible measure may capture a broader range of disadvantage. We find that multidimensional deprivation constitutes a fundamental barrier to educational access: children deprived across multiple dimensions—whether measured strictly or flexibly—are systematically less likely to attend formal schooling, underscoring the need for integrated, multi-sectoral strategies to enhance educational inclusion. Empirical studies show that when educational, health and living-standard deprivations overlap, school participation falls sharply (see e.g. Bukhari, Lean, Bukhari, Raza, and Pervaiz (2024)). Moreover, policy analyses emphasise that effective educational inclusion interventions must be paired with poverty measurement frameworks that identify composite disadvantage, enabling targeted programmes beyond single-sector solutions.

Table 5 reports the heterogeneous effects of multidimensional deprivation on school attendance across gender, caste, religion, and sectoral subgroups. The results confirm a consistently negative relationship across nearly all categories, though the magnitude of the effect varies. Both male and female children exhibit similar sensitivity to deprivation, indicating that early-life deprivation constrains school participation irrespective of gender. Across caste groups, the odds ratios indicate stronger marginal penalties among OBC and General category children relative to SC and ST groups, suggesting that deprivation exerts a larger marginal effect where baseline access to schooling is relatively higher. Religious differences are also evident, with Muslim and other minority children displaying weaker odds of school attendance associated with higher deprivation levels compared to Hindu children.

Literature on Indian educational inequality shows that children from SC/ST, OBC and Muslim households remain significantly more likely to be excluded from schooling, even after controlling for socioeconomic factors (see (M. K. Garg, Chowdhury, & SK, 2022; Dunn, 1993)). Sectoral differences

further underline the context-specific nature of deprivation effects, with urban children facing a sharper relative penalty associated with deprivation than their rural counterparts. Aligning with research on multidimensional deprivation, studies find that relative disadvantage in urban spaces can in some cases widen educational exclusion gaps between deprived and non-deprived groups (see (S. Garg & Mishra, 2024)). These patterns highlight the need for intersection-sensitive policy frameworks that recognise how deprivation effects are amplified among historically marginalised identity groups.

Deprivation on Educational Outcome

Table 6 examines how multidimensional deprivation shapes children's learning outcomes at age eight under both strict and flexible deprivation definitions. Across all learning measures—PPVT, Mathematics, and EGRA—the coefficients on childhood multidimensional deprivation (CMD) are negative and highly statistically significant across estimation strategies, reaffirming the robustness of the relationship between early deprivation and diminished learning performance. Given that both outcome and deprivation measures are standardized, the estimates can be interpreted as standard deviation effects. A one standard deviation increase in CMD is associated with a decline of approximately 0.12–0.16 standard deviations in learning outcomes under OLS, while the IV and Control Function estimates indicate substantially larger effects, ranging from about 0.37 to 0.63 standard deviations depending on the outcome and deprivation definition. These results underscore that multidimensional deprivation imposes a substantial penalty on children's cognitive, language, and numeracy development, consistent with evidence from Fink and Rockers (2014) and Soni et al. (2021), who document strong links between early-life adversity, undernutrition, and lower learning achievement among Indian children.

The similarity of estimates under both strict and flexible deprivation definitions highlights the structural nature of deprivation's impact on learning. Regardless of how deprivation is measured, it consistently undermines children's cognitive and academic performance. Parental education emerges as an important mitigating factor across specifications, with both mother's and father's education displaying positive and statistically significant associations with learning outcomes. Maternal education, in particular, exerts a stronger influence, suggesting that maternal human capital plays a critical role in shaping early learning environments through caregiving quality and cognitive stimulation. This pattern aligns closely with findings from Upadhyay, Srivastava, and Paul (2018) and Singh and Sarkar (2014), who show that higher maternal education significantly improves PPVT, EGRA, and mathematics outcomes among disadvantaged children.

Table 6 further reports causal estimates obtained using Instrumental Variables (IV) and Control Function (CF) approaches to address potential endogeneity of deprivation. While OLS estimates indi- cate moderate negative associations, the IV and CF coefficients are substantially larger in magnitude and remain highly significant across all outcomes and deprivation definitions. This systematic divergence suggests that conventional regression approaches underestimate the true impact of deprivation due to endogeneity arising from unobserved household characteristics and measurement error. The consis- tency between IV and CF estimates strengthens confidence in the causal interpretation of the results and indicates that early-life deprivation exerts a deeper and more persistent influence on learning outcomes than suggested by naıve estimates.

Differences across learning domains are also evident. For language (PPVT) and numeracy (Mathematics), the flexible deprivation definition yields slightly larger causal effects than the strict definition, indicating that broader measures of deprivation capture more comprehensive developmental disadvantages. Reading outcomes (EGRA), while also negatively affected, exhibit relatively smaller magnitudes, suggesting some domain-specific resilience or differential sensitivity to early deprivation. Nonetheless, the direction and statistical significance of the effects remain consistent across all domains, reinforcing the conclusion that multidimensional deprivation systematically constrains children's learning potential. Table 7 presents diagnostic tests supporting the validity of the instrumental variable strategy. The Kleibergen–Paap first-stage F-statistics exceed the Stock–Yogo 10% maximal bias threshold of 19.93 across all outcomes and deprivation definitions, indicating that the instruments—mother's and father's education—are sufficiently strong. The Kleibergen–Paap LM tests reject underidentification at the 1% level in all cases, confirming proper model identification. Endogeneity tests reject the null of exogeneity for PPVT and Mathematics outcomes under both deprivation definitions, while evidence of endogeneity is weaker for EGRA. Hansen J-tests generally fail to reject the null of instrument validity, with only marginal concern in the strict numeracy specification. Taken together, these diagnostics provide strong support for the reliability of the IV and CF estimates reported.

Despite the strength of the causal estimates, the IV coefficients should be interpreted cautiously as upper-bound effects, given the moderate explanatory power of the instruments. Nevertheless, the consistency in sign, magnitude, and statistical significance across outcomes, estimation strategies, and deprivation definitions provides compelling evidence that childhood multidimensional deprivation has a substantial and enduring negative effect on later learning performance. The results suggest that addressing overlapping deprivations in early life is essential for improving cognitive and educational outcomes, particularly in contexts characterised by persistent socioeconomic disadvantage.

Heterogeneity Analysis of Outcome Impacts

To further unpack the causal relationship between childhood multidimensional deprivation (CMD) and learning outcomes, Tables 8–13 present subgroup-specific results across gender, location, religion, and caste. The heterogeneity analysis reveals substantial variation in the magnitude of deprivation effects across social and demographic groups, indicating that structural and contextual factors mediate the extent to which early-life disadvantage translates into later learning deficits.

Table 8 provides a consolidated summary of the instrumental variable estimates across all subgroups and learning domains. Across gender, sector, religion, and caste categories, CMD exhibits a consistently negative and statistically significant effect on language (PPVT), numeracy (Math), and reading (EGRA) outcomes. Given that both deprivation and learning measures are standardized, the coefficients can be interpreted as standard deviation effects. The summary evidence indicates that a one standard deviation increase in childhood deprivation is associated with declines ranging roughly from 0.3 to 0.9 standard deviations in learning outcomes, with larger magnitudes observed for language and numeracy relative to reading. While the direction of effects is uniform, the size of the coefficients varies considerably across subgroups, underscoring the uneven distribution of deprivation penalties.

Gender-based heterogeneity results reported in Table 9 reveal pronounced differences in the causal impact of deprivation. Female children experience substantially larger negative effects than male children across all learning domains and both deprivation definitions. Under the strict definition, the IV estimates for girls exceed 0.7 standard deviations for PPVT and Math, compared to effects of approx- imately 0.4–0.5 standard deviations for boys. Although the magnitude of effects declines slightly un- der the flexible definition, the gender gap persists across language, numeracy, and reading outcomes. These patterns suggest that multidimensional deprivation interacts with existing gender inequalities, compounding disadvantages for girls during critical stages of cognitive and skill development.

Location-based heterogeneity, presented in Table 10, shows that both urban and rural children suf- fer significant learning penalties associated with deprivation, though the magnitude differs by context. Urban children exhibit slightly larger negative effects for numeracy and reading, with IV estimates approaching 0.7–0.8 standard deviations under the strict definition. Rural children also experience sizable and statistically significant effects, particularly for language and numeracy, though the magnitudes are somewhat smaller on average. These results indicate that urban residence does not insulate children from the cognitive consequences of deprivation and that relative deprivation within urban settings may carry particularly high learning costs.

Religious heterogeneity results in Table 11 point to stark differences between Hindu and Muslim children. While CMD negatively affects learning outcomes for both groups, the magnitude of effects is consistently larger for Muslim children across all domains and deprivation definitions. The IV estimates for Muslim children frequently exceed 0.7–0.8 standard deviations for PPVT and Math, substantially larger than the corresponding effects among Hindu children. These findings highlight how socioeconomic deprivation and religious marginalization interact, intensifying learning losses through compounded disadvantages related to access, segregation, and institutional exclusion.

Caste-based heterogeneity is examined in Tables 12 and 13. Scheduled Tribe (ST) children experience the strongest deprivation effects across all learning outcomes, with IV coefficients often exceeding 0.6–1.0 standard deviations, reflecting deep-rooted structural isolation and limited access to quality educational inputs. In contrast, Scheduled Caste (SC) children show weaker and often statistically in- significant effects, particularly for numeracy and reading, potentially reflecting the partial buffering role of affirmative action policies and improved schooling access in some regions. Other Backward Classes (OBC) experience moderate but robust negative effects across domains, while children from other caste groups also exhibit large and statistically significant coefficients, indicating that early-life deprivation can substantially depress learning outcomes even among relatively advantaged social strata.

The heterogeneity analysis reinforces the central conclusion that childhood multidimensional deprivation has a large and persistent negative impact on learning outcomes, while also demonstrating that these effects are far from uniform. As summarized in Table 8, deprivation penalties are systematically larger for girls, Muslim children, Scheduled Tribes, and urban residents, suggesting that CMD amplifies pre-existing social hierarchies and institutional inequalities. These patterns underscore the need for targeted, group-sensitive policy interventions that address both material deprivation and the social contexts through which disadvantage is transmitted into unequal human capital formation.

7. POLICY IMPLICATIONS

The findings offer several important policy implications for addressing multidimensional deprivation and its lasting effects on children's education in Andhra Pradesh and Telangana.

First, existing multidimensional poverty frameworks, including those adopted by the UNDP and national measures, often rely on unrealistic and outdated deprivation labels. For instance, the education dimension typically classifies deprivation merely by literacy status, which fails to capture the depth of educational attainment in a context where basic literacy no longer ensures meaningful human capital or employment opportunities. As the overall educational attainment levels in India—and particularly in

Andhra Pradesh and Telangana—continue to rise, policy frameworks must revise these thresholds to reflect contemporary realities. The evidence from the differences in coefficients under strict and flexible deprivation measures underscores this point, showing that the severity of deprivation intensifies when broader, more realistic criteria are applied.

Second, despite the presence of extensive social protection and child welfare schemes—such as maternal health, nutrition, and school-based programs—the persistence of strong and significant deprivation effects highlights the need to strengthen early childhood interventions. Policies should focus on enhancing the quality and continuity of early education, addressing health and nutritional deficits before school entry, and integrating family-based support systems. A dynamic approach that gradually lifts the deprivation cut-offs over time would ensure that policy targets remain relevant, capturing relative rather than only absolute forms of child poverty.

Third, policy efforts should combine maternal education and awareness initiatives with programs aimed at improving school readiness and foundational learning. Maternal education consistently emerges as a critical determinant of children's cognitive and language outcomes. Integrating parental awareness with early-grade learning interventions would reinforce home–school linkages and enhance children's readiness to benefit from formal education.

Finally, the persistent disadvantages observed among rural and marginalized social groups call for renewed policy attention to equity in educational access. Despite overall improvements in enrollment, children from disadvantaged castes and rural areas continue to lag behind their urban and upper-caste counterparts. Ensuring inclusive educational development therefore requires targeted investments in rural schooling infrastructure, teacher quality, and community-level engagement to prevent the intergenerational transmission of deprivation among children.

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Table 1 Description and Categorization of Variables

Variable	*Description*	*Type*	*Category*
Peabody Picture Vocabulary Test (PPVT) Score	Standardized Rasch index of receptive vocabulary (corrected)	Continuous	Learning outcome
Mathematics Achievement Score	Standardized Rasch score for mathematics test (corrected)	Continuous	Learning outcome
Early Grade Reading Assessment (EGRA) Score	Global Rasch factor score from the EGRA literacy test	Continuous	Learning outcome
Cognitive Development Assessment (CDA) Score	Rasch score capturing cognitive learning performance	Continuous	Learning outcome
PPVT Language Score (Round 5)	Rasch score in PPVT language test from earlier survey round	Continuous	Learning outcome
Formal School Attendance	Indicates whether the child ever attended formal school (Yes=1, No=0)	Binary	School participation
Strict Deprivation Index	Composite multidimensional deprivation score under strict definition	Continuous	Key explanatory variable
Flexible Deprivation Index	Composite multidimensional deprivation score under flexible definition	Continuous	Key explanatory variable
Gender of Child	Male = 1; Female = 2	Categorical	Demographic
Sector of Residence	Urban = 1; Rural = 2	Categorical	Socioeconomic
Survey Round	Survey wave identifier (Round 3)	Constant	Survey characteristic
Region	Telangana = 0; Andhra Pradesh = 1	Categorical	Geographic
Religion	Hindu = 1; Other religions = 0	Categorical	Demographic
Caste Group	Scheduled Caste = 21; Scheduled Tribe = 22; OBC = 23; Others = 24	Categorical	Social group
Mother's Education	Years of completed education by mother	Continuous	Parental background
Father's Education	Years of completed education by father	Continuous	Parental background
Birth Weight	Child's birth weight measured in grams	Continuous	Health instrument

Table 2: Summary Statistics

VARIABLE	N	MEAN	SD	MIN	MAX
SCHOOL ENROLLMENT	1930	0.99	0.099	0	1
PPVT SCORE	1931	301.121	15.256	238.7	358.7
MATH SCORE	1931	299.939	14.972	258.8	342.5
EGRA SCORE	1931	299.844	14.983	263.3	361.9
DEPRIVATION (FLEXIBLE)	1928	0.194	0.094	0	0.455
DEPRIVATION (STRICT)	1928	0.22	0.081	0	0.455
FATHER'S EDUCATION	1930	6.201	6.203	0	28
MOTHER'S EDUCATION	1930	4.363	6.052	0	29
HINDU	1930	0.919	0.273	0	1
MUSLIM	1930	0.072	0.259	0	1
OTHER RELIGION	1930	0.009	0.096	0	1
URBAN	1930	0.253	0.435	0	1
RURAL	1930	0.747	0.435	0	1
SCHEDULED CASTE	1930	0.181	0.385	0	1
SCHEDULED TRIBE	1930	0.129	0.335	0	1
OBC	1930	0.481	0.5	0	1
OTHER CASTES	1930	0.209	0.407	0	1
MALE	1930	0.532	0.499	0	1
FEMALE	1930	0.468	0.499	0	1

Table 3: Mean Test Scores by Demographic Groups

GROUP	PPVT (MEAN (SD))	MATH (MEAN (SD))	EGRA (MEAN (SD))
SC	300.54 (14.58)	298.82 (14.79)	300.17 (15.39)
ST	295.52 (13.56)	291.71 (14.73)	295.50 (13.41)
OBC	300.36 (15.18)	300.48 (14.41)	299.42 (14.55)
OTHERS	306.89 (15.25)	304.81 (14.27)	303.23 (15.78)
MALE	302.71 (15.39)	300.04 (14.77)	299.30 (14.98)
FEMALE	299.35 (14.91)	299.87 (15.18)	300.47 (14.98)
HINDU	300.75 (15.15)	300.16 (14.98)	300.08 (14.98)
NON-HINDU	305.44 (15.77)	297.60 (14.56)	297.24 (14.82)
URBAN	308.26 (15.09)	302.40 (13.44)	301.20 (14.62)
RURAL	298.72 (14.54)	299.13 (15.35)	299.39 (15.09)
OVERALL MEAN	301.13 (15.25)	299.96 (14.96)	299.85 (14.99)

Table 4: Regression Results for Strict vs. Flexible Models

SPECIFICATION	LOGIT (1) STRICT	LOGIT (2) FLEXIBLE	FIRTH LOGIT (3) STRICT	FIRTH LOGIT (4) FLEXIBLE
CMD (ODDS RATIO)	0.134***	0.100***	0.156***	0.116***
	(0.099)	(0.077)	(0.050)	(0.043)
CMD (AME)	-0.018***	-0.021***	-1.859***	-2.151***
	(0.005)	(0.005)	(0.323)	(0.367)
OBSERVATIONS	1,910	1,910	1,928	1,928
PSEUDO R-SQUARED	0.275	0.286		
LOG LIKELIHOOD	-77.193	-76.019	-68.170	-66.932

Table 5: Heterogeneity Analysis: Odds Ratios of CMD across Subgroups

Group	***Strict (1)***	***Flexible (2)***	***Strict (3)***	***Flexible (4)***
Panel A: Location				
Urban	0.102** (0.102)	0.064*** (0.064)		
Rural			0.195*** (0.069)	0.142*** (0.057)
Observations (Location)	**488**	**488**	**1,440**	**1,440**
Panel B: Gender				
Male	0.111*** (0.062)	0.091*** (0.057)		
Female			0.206*** (0.080)	0.151*** (0.066)
Observations (Gender)	**1,025**	**1,025**	**903**	**903**
Panel C: Social Groups				
Scheduled Caste (SC)	0.322* (0.205)	0.239* (0.179)		
Scheduled Tribe (ST)			0.315 (0.262)	0.337 (0.297)
Observations (SC/ST)	349	349	248	248
Other Backward Classes (OBC)	0.163*** (0.073)	0.096*** (0.051)		
Others			0.162* (0.170)	0.144* (0.167)
Observations (OBC/Others)	**928**	**928**	**403**	**403**
Panel D: Religion				
Hindu	0.178*** (0.062)	0.128*** (0.051)		
Muslim & Others			0.204 (0.213)	0.208* (0.188)
Observations (Religion)	**1,771**	**1,771**	**157**	**157**

Table 6: Impact of Multidimensional Deprivation on Learning Outcomes at Age 8

Specification	*Strict OLS (1)*	*Strict IV (2)*	*Strict CF (3)*	*Flexible OLS (4)*	*Flexible IV (5)*	*Flexible CF (6)*
Panel A: PPVT (Language)						
CMD	-0.116***	-0.634***	-0.634***	-0.151***	-0.542***	-0.542***
	(0.027)	(0.085)	(0.125)	(0.030)	(0.068)	(0.098)
N	1,928	1,928	1,928	1,928	1,928	1,928
R2	0.212	0.066	0.211	0.216	0.144	0.214
Panel B: Math (Numeracy)						
CMD	-0.124***	-0.622***	-0.622***	-0.160***	-0.532***	-0.532***
	(0.034)	(0.073)	(0.110)	(0.035)	(0.060)	(0.085)
N	1,928	1,928	1,928	1,928	1,928	1,928
R2	0.208	0.071	0.205	0.211	0.145	0.209
Panel C: EGRA (Reading)						
CMD	-0.130***	-0.429***	-0.429***	-0.142***	-0.367***	-0.367***
	(0.042)	(0.092)	(0.133)	(0.044)	(0.077)	(0.108)
N	1,928	1,928	1,928	1,928	1,928	1,928
R2	0.132	0.082	0.130	0.133	0.108	0.131
F-statistic (IV)	**–**	**27.16**	**27.16**	**–**	**23.27**	**23.27**

Table 7: Comprehensive IV Diagnostics for Childhood Deprivation Models (Age 8)

Panel	*Outcome*	*First-stage F (KP rk)*	*Cragg–Donald Wald F*	*Endogeneity F (p-value)*	*KP LM (p-value)*	*Hansen J (p-value)*
Strict Definition	PPVT (Language)	26.93	128.95	14.58 (0.0012)	0.0003	0.1597
Strict Definition	Math (Numeracy)	27.26	206.92	21.69 (0.0002)	0.0002	0.0491
Strict Definition	EGRA (Reading)	27.38	210.68	3.60 (0.0729)	0.0002	0.1363
Flexible Definition	PPVT (Language)	20.73	224.4	12.92 (0.0019)	0.0001	0.2468
Flexible Definition	Math (Numeracy)	22.75	335.21	15.33 (0.0009)	0.0001	0.0943
Flexible Definition	EGRA (Reading)	22.9	337.05	2.46 (0.1333)	0.0001	0.2041

Table 8: Summary of CMD Effects Across Subgroups and Learning Outcomes (Age 8)

Subgroup	*PPVT Strict*	*PPVT S.E.*	*PPVT Flexible*	*PPVT S.E.*	*Math Strict*	*Math S.E.*	*Math Flexible*	*Math S.E.*	*EGRA Strict*	*EGRA S.E.*	*EGRA Flexible*	*EGRA S.E.*
Male	-0.455**	(0.147)	-0.365***	(0.114)	-0.483***	(0.085)	-0.391***	(0.064)	-0.333***	(0.068)	-0.273***	(0.090)
Female	-0.867***	(0.125)	-0.730***	(0.088)	-0.797***	(0.097)	-0.719***	(0.072)	-0.548***	(0.087)	-0.460***	(0.091)
Urban	-0.636***	(0.151)	-0.553***	(0.120)	-0.761***	(0.134)	-0.738***	(0.077)	-0.686***	(0.141)	-0.676***	(0.101)
Rural	-0.615***	(0.134)	-0.495***	(0.095)	-0.551***	(0.096)	-0.451***	(0.067)	-0.270**	(0.114)	-0.223**	(0.088)
Hindu	-0.650***	(0.075)	-0.572***	(0.058)	-0.627***	(0.078)	-0.860***	(0.247)	-0.440***	(0.066)	-0.760***	(0.286)
Muslim	-0.807***	(0.184)	-0.680***	(0.150)	-0.860***	(0.247)	-0.860***	(0.247)	-0.760***	(0.286)	-0.760***	(0.286)
SC	-0.461**	(0.201)	-0.352**	(0.177)	-0.336	(0.245)	-0.229	(0.208)	-0.081	(0.206)	-0.040	(0.155)
ST	-0.638***	(0.085)	-0.554***	(0.072)	-0.767***	(0.100)	-0.657***	(0.062)	-0.674***	(0.079)	-0.579***	(0.069)
OBC	-0.704***	(0.070)	-0.612***	(0.045)	-0.593***	(0.083)	-0.516***	(0.068)	-0.422***	(0.089)	-0.368***	(0.077)
Others	-0.710***	(0.123)	-0.675***	(0.112)	-0.737***	(0.173)	-0.692***	(0.153)	-0.641***	(0.138)	-0.605***	(0.129)

Table 9: Heterogeneity by Gender: Impact of Multidimensional Deprivation on Learning Outcomes at Age 8

	STRICT DEFINITION						**FLEXIBLE DEFINITION**					
	OLS	**S.E.**	**IV**	**S.E.**	**CF**	**S.E.**	**OLS**	**S.E.**	**IV**	**S.E.**	**CF**	**S.E.**
PANEL A: MALE SUBGROUP												
PPVT (LANGUAGE)												
CMD	-0.099*	(0.040)	-0.455**	(0.147)	-0.407*	(0.150)	-0.141***	(0.040)	-0.365***	(0.114)	-0.345***	(0.119)
N	818		818		818		818		818		818	
R2	0.203		0.135		0.203		0.206		0.183		0.206	
MATH (NUMERACY)												
CMD	-0.218***	(0.051)	-0.483***	(0.085)	-0.481***	(0.070)	-0.130***	(0.045)	-0.391***	(0.064)	-0.391***	(0.074)
N	1008		1008		1008		1008		1008		1008	
R2	0.050		.		0.082		0.202		0.170		0.201	

EGRA (READING)												
CMD	-0.161***	(0.049)	-0.333***	(0.068)	-0.337***	(0.082)	-0.111	(0.067)	-0.273***	(0.090)	-0.274**	(0.108)
N	981		981		981		981		981		981	
R2	0.027		.		0.041		0.136		0.123		0.135	
FIRST-STAGE F	–		19.23		19.23		–		20.53		20.53	
PANEL B: FEMALE SUBGROUP												
PPVT (LANGUAGE)												
CMD	-0.112*	(0.049)	-0.867***	(0.125)	-0.761***	(0.126)	-0.142**	(0.055)	-0.730***	(0.088)	-0.667***	(0.099)
N	768		768		768		768		768		768	
R2	0.193		–		0.190		0.196		0.019		0.194	
MATH (NUMERACY)												
CMD	-0.308***	(0.058)	-0.797***	(0.097)	-0.791***	(0.110)	-0.189***	(0.041)	-0.719***	(0.072)	-0.709***	(0.118)
N	893		893		893		893		893		893	
R2	0.087		–		0.151		0.244		0.117		0.241	
EGRA (READING)												
CMD	-0.239***	(0.043)	-0.548***	(0.087)	-0.556***	(0.127)	-0.188***	(0.047)	-0.460***	(0.091)	-0.467***	(0.136)
N	870		870		870		870		870		870	
R2	0.055		0.067		0.083		0.146		0.110		0.145	
FIRST-STAGE F	–		17.64		17.64		–		14.32		14.32	

Table 10: Heterogeneity by Location: Impact of Multidimensional Deprivation on Learning Outcomes at Age 8

	Strict Definition						***Flexible Definition***					
	OLS	**S.E.**	**IV**	**S.E.**	**CF**	**S.E.**	**OLS**	**S.E.**	**IV**	**S.E.**	**CF**	**S.E.**
						Panel A: Urban Subgroup						
PPVT (Language)												
CMD	-0.160**	(0.099)	-0.636***	(0.151)	-0.595***	(0.102)	-0.152**	(0.094)	-0.553***	(0.120)	-0.556***	(0.104)
N	295		295		295		295		295		295	
R2	0.161		0.057		0.160		0.157		0.101		0.155	
Math (Numeracy)												
CMD	-0.142***	(0.042)	-0.761***	(0.134)	-0.753***	(0.052)	-0.101**	(0.064)	-0.738***	(0.077)	-0.728***	(0.051)
N	480		480		480		480		480		480	
R2	0.271		0.090		0.270		0.264		0.130		0.264	
EGRA (Reading)												
CMD	-0.089**	(0.057)	-0.686***	(0.141)	-0.701***	(0.094)	-0.040**	(0.051)	-0.676***	(0.101)	-0.682***	(0.092)
N	461		461		461		461		461		461	
R2	0.201		0.052		0.200		0.198		0.047		0.198	
First-stage F	–		15.74		15.74		–		85.70		85.70	
						Panel B: Rural Subgroup						
PPVT (Language)												
CMD	-0.087**	(0.034)	-0.615***	(0.134)	-0.561***	(0.155)	-0.128***	(0.038)	-0.495***	(0.095)	-0.462***	(0.116)
N	1,291		1,291		1,291		1,291		1,291		1,291	
R2	0.168		.		0.166		0.173		0.099		0.171	
Math (Numeracy)												
CMD	-0.095**	(0.041)	-0.551***	(0.096)	-0.552***	(0.128)	-0.150***	(0.041)	-0.451***	(0.067)	-0.450***	(0.090)
N	1,421		1,421		1,421		1,421		1,421		1,421	
R2	0.205		0.091		0.203		0.211		0.166		0.209	
EGRA (Reading)												
CMD	-0.112**	(0.046)	-0.270**	(0.114)	-0.275*	(0.143)	-0.155***	(0.046)	-0.223**	(0.088)	-0.225**	(0.103)
N	1,390		1,390		1,390		1,390		1,390		1,390	

R2	0.140	0.126	0.139	0.145	0.142	0.144
First-stage F	–	22.25	22.25	–	17.55	17.55

Table 11: Heterogeneity by Religion: Impact of CMD on Learning Outcomes at Age 8

	Strict Definition			Flexible Definition		
	OLS	IV (2SLS)	CF	OLS	IV (2SLS)	CF
Panel A: Hindu Subgroup						
PPVT (Language)						
CMD	-0.306***	-0.650***	-0.574***	-0.349***	-0.572***	-0.539***
	(0.041)	(0.075)	(0.063)	(0.036)	(0.058)	(0.056)
N	1,771	1,771	1,771	1,771	1,771	1,771
R^2	0.094	–	0.151	0.121	0.072	0.160
Math (Numeracy)						
CMD	-0.275***	-0.627***	-0.476***	-0.300***	-0.860***	-0.392***
	(0.048)	(0.078)	(0.082)	(0.080)	(0.247)	(0.111)
N	1,771	1,771	1,771	1,771	1,771	1,771
R^2	0.075	–	0.106	0.065	–	0.071
EGRA (Reading)						
CMD	-0.206***	-0.440***	-0.317***	-0.234**	-0.760***	-0.150
	(0.042)	(0.066)	(0.074)	(0.105)	(0.286)	(0.102)
N	1,771	1,771	1,771	1,771	1,771	1,771
R^2	0.042	–	0.052	0.038	–	0.043
First-stage *F*	–	**25.70**	**25.70**	–	**20.74**	**20.74**
Panel B: Muslim Subgroup						
PPVT (Language)						
CMD	-0.516***	-0.807***	-0.603***	-0.425***	-0.680***	-0.553***
	(0.070)	(0.184)	(0.074)	(0.092)	(0.150)	(0.072)
N	157	157	157	157	157	157
R^2	0.170	0.116	0.174	0.111	0.071	0.124
Math (Numeracy)						
CMD	-0.300***	-0.860***	-0.392***	-0.300***	-0.860***	-0.392***
	(0.080)	(0.247)	(0.111)	(0.080)	(0.247)	(0.111)
N	157	157	157	157	157	157
R^2	0.065	–	0.071	0.065	–	0.071
EGRA (Reading)						
CMD	-0.234**	-0.760***	-0.150	-0.234**	-0.760***	-0.150
	(0.105)	(0.286)	(0.102)	(0.105)	(0.286)	(0.102)
N	157	157	157	157	157	157
R^2	0.038	–	0.043	0.038	–	0.043
First-stage *F*	–	**14.28**	**14.28**	–	**17.04**	**17.04**

Table 12: Heterogeneity by Caste (SC & OBC): Impact of CMD on Learning Outcomes at Age 8

	Strict Definition			Flexible Definition		
	OLS	IV (2SLS)	CF	OLS	IV (2SLS)	CF
Panel A: Scheduled Caste (SC)						
PPVT (Language)						
CMD	-0.223**	-0.461**	-0.381**	-0.240**	-0.352**	-0.340**
	(0.090)	(0.201)	(0.153)	(0.099)	(0.177)	(0.136)
N	349	349	349	349	349	349
R^2	0.039	–	0.052	0.046	0.036	0.053
Math (Numeracy)						
CMD	-0.083	-0.336	-0.119	-0.121	-0.229	-0.125
	(0.082)	(0.245)	(0.132)	(0.090)	(0.208)	(0.126)
N	349	349	349	349	349	349
R^2	0.005	–	0.006	0.011	0.002	0.011
EGRA (Reading)						
CMD	-0.039	-0.081	-0.003	-0.059	-0.040	-0.011
	(0.086)	(0.206)	(0.130)	(0.084)	(0.155)	(0.119)
N	349	349	349	349	349	349
R^2	0.001	–	0.002	0.002	0.002	0.004
First-stage *F*	–	**19.96**	**19.96**	–	**13.04**	**13.04**
Panel B: Other Backward Classes (OBC)						
PPVT (Language)						
CMD	-0.320***	-0.704***	-0.651***	-0.367***	-0.612***	-0.597***
	(0.055)	(0.070)	(0.077)	(0.047)	(0.045)	(0.068)
N	928	928	928	928	928	928
R^2	0.094	–	0.165	0.124	0.068	0.171
Math (Numeracy)						
CMD	-0.230***	-0.593***	-0.368***	-0.261***	-0.516***	-0.353***
	(0.049)	(0.083)	(0.087)	(0.042)	(0.068)	(0.075)
N	928	928	928	928	928	928
R^2	0.052	–	0.065	0.067	0.002	0.075
EGRA (Reading)						
CMD	-0.192***	-0.422***	-0.273**	-0.210***	-0.368***	-0.262***
	(0.048)	(0.089)	(0.097)	(0.047)	(0.077)	(0.087)
N	928	928	928	928	928	928
R^2	0.035	–	0.040	0.043	0.019	0.045
First-stage *F*	–	**24.13**	**24.13**	–	**15.39**	**15.39**

Table 13: Heterogeneity by Caste (ST & Other Castes): Impact of CMD on Learning Outcomes at Age 8

	Strict Definition			Flexible Definition		
	OLS	IV (2SLS)	CF	OLS	IV (2SLS)	CF
Panel A: Scheduled Tribe (ST)						
PPVT (Language)						
CMD	-0.290***	-0.638***	-1.010***	-0.330***	-0.554***	-0.885***
	(0.035)	(0.085)	(0.173)	(0.035)	(0.072)	(0.161)
N	248	248	248	248	248	248
R^2	0.096	–	0.191	0.120	0.065	0.190
Math (Numeracy)						
CMD	-0.284***	-0.767***	-1.082***	-0.332***	-0.657***	-0.973***
	(0.077)	(0.100)	(0.199)	(0.069)	(0.062)	(0.185)
N	248	248	248	248	248	248
R^2	0.075	–	0.170	0.099	0.004	0.175
EGRA (Reading)						
CMD	-0.258***	-0.674***	-0.738***	-0.306***	-0.579***	-0.669***
	(0.047)	(0.079)	(0.234)	(0.043)	(0.069)	(0.202)
N	248	248	248	248	248	248
R^2	0.075	–	0.116	0.102	0.021	0.131
First-stage *F*	–	**76.59**	**76.59**	–	**28.91**	**28.91**
Panel B: Other Castes						
PPVT (Language)						
CMD	-0.247***	-0.710***	-0.405***	-0.259**	-0.675***	-0.409***
	(0.085)	(0.123)	(0.113)	(0.093)	(0.112)	(0.104)
N	403	403	403	403	403	403
R^2	0.054	–	0.069	0.051	–	0.069
Math (Numeracy)						
CMD	-0.142*	-0.737***	-0.166	-0.159**	-0.692***	-0.197*
	(0.072)	(0.173)	(0.129)	(0.072)	(0.153)	(0.113)
N	403	403	403	403	403	403
R^2	0.020	–	0.020	0.021	–	0.022
EGRA (Reading)						
CMD	-0.125**	-0.641***	-0.122	-0.093	-0.605***	-0.150
	(0.056)	(0.138)	(0.121)	(0.055)	(0.129)	(0.107)
N	403	403	403	403	403	403
R^2	0.013	–	0.013	0.006	–	0.008
First-stage *F*	–	**16.27**	**16.27**	–	**19.48**	**19.48**

A FIGURES

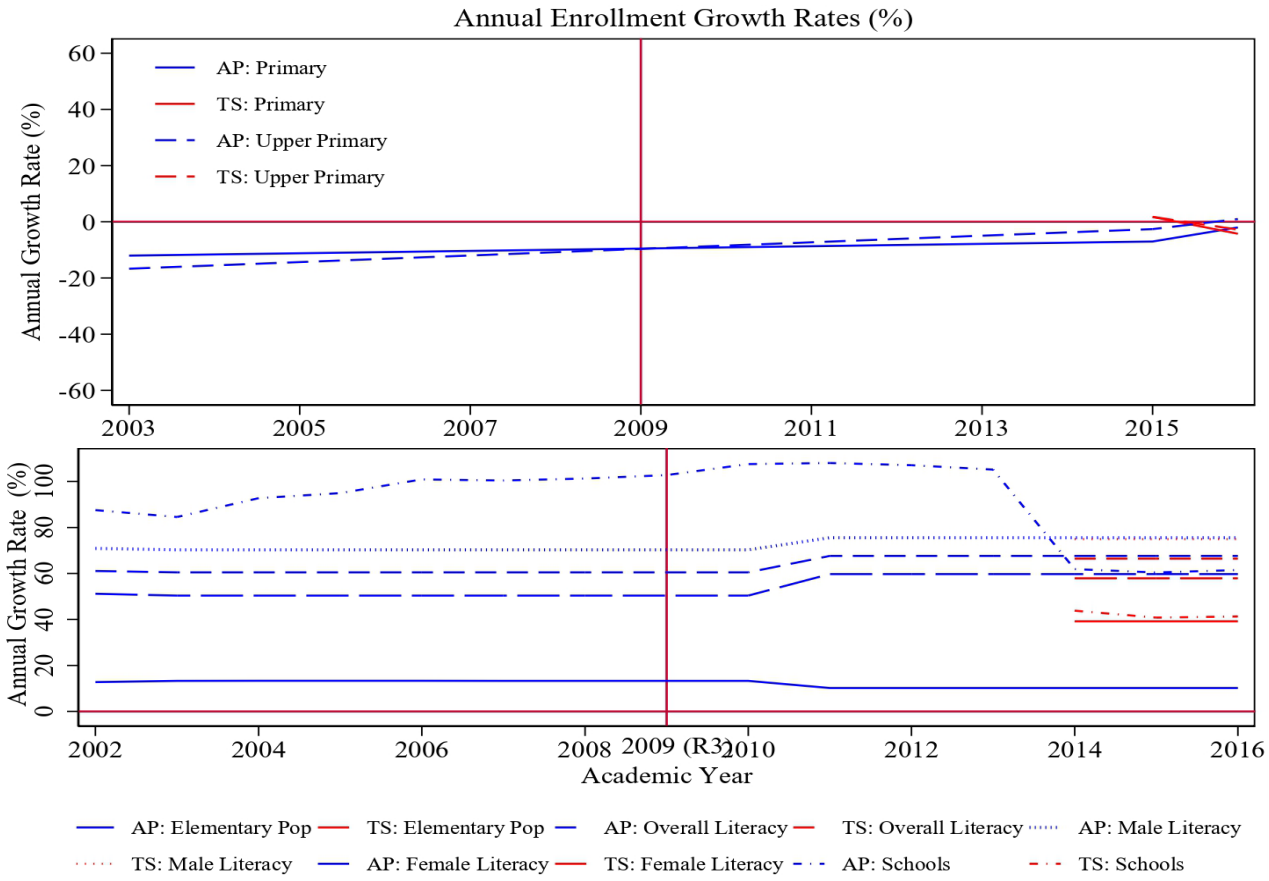


Figure 1: Annual Enrollment and Literacy Trends in Andhra Pradesh and Telangana

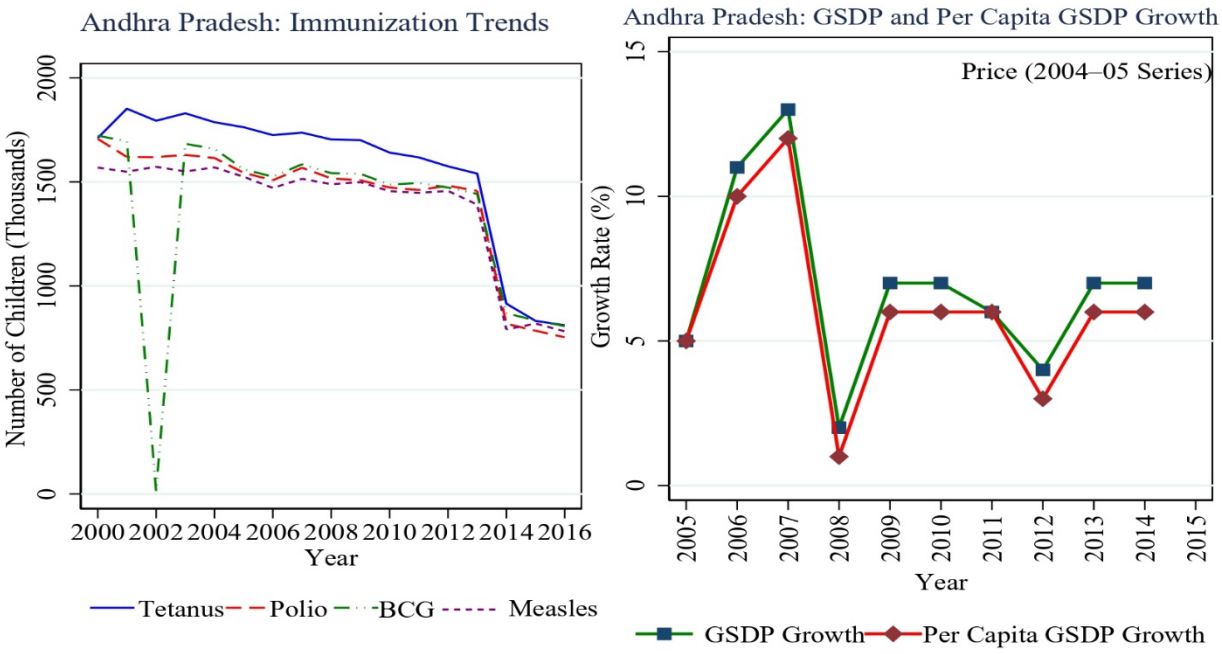


Figure 2: Socioeconomic and Health Indicators in Andhra Pradesh: 2000–2016

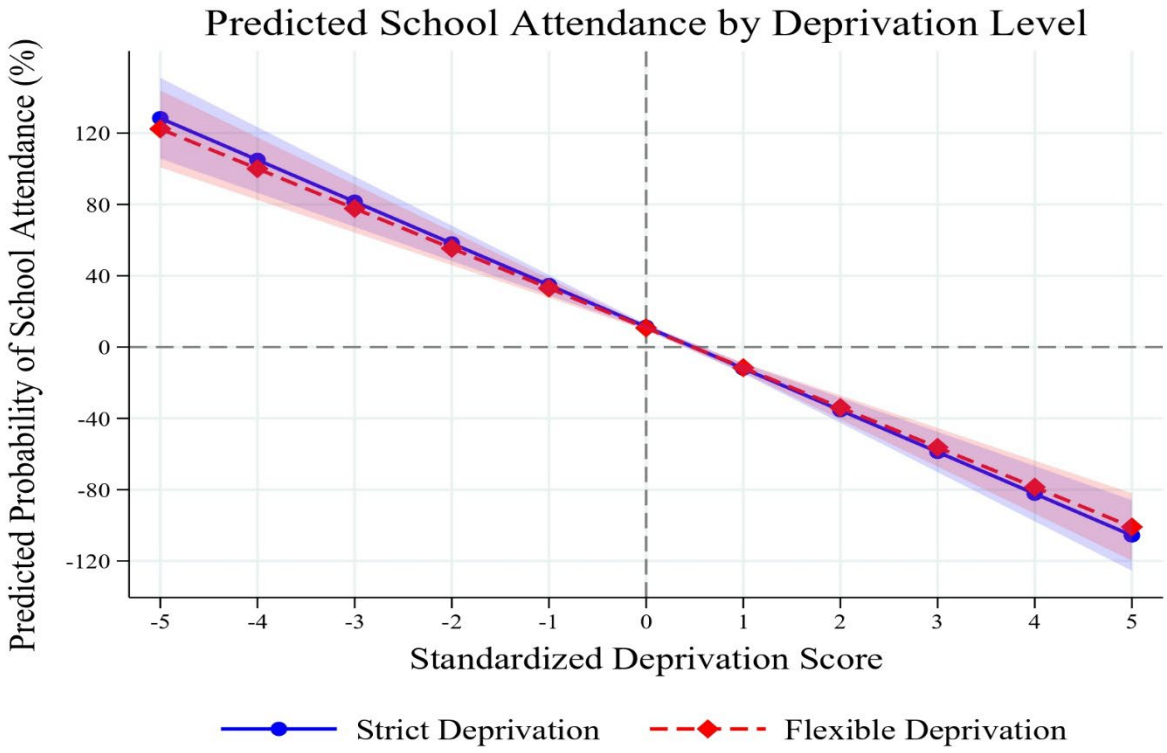


Figure 3: Predicted Probabilities of School Attendance by Deprivation Level.

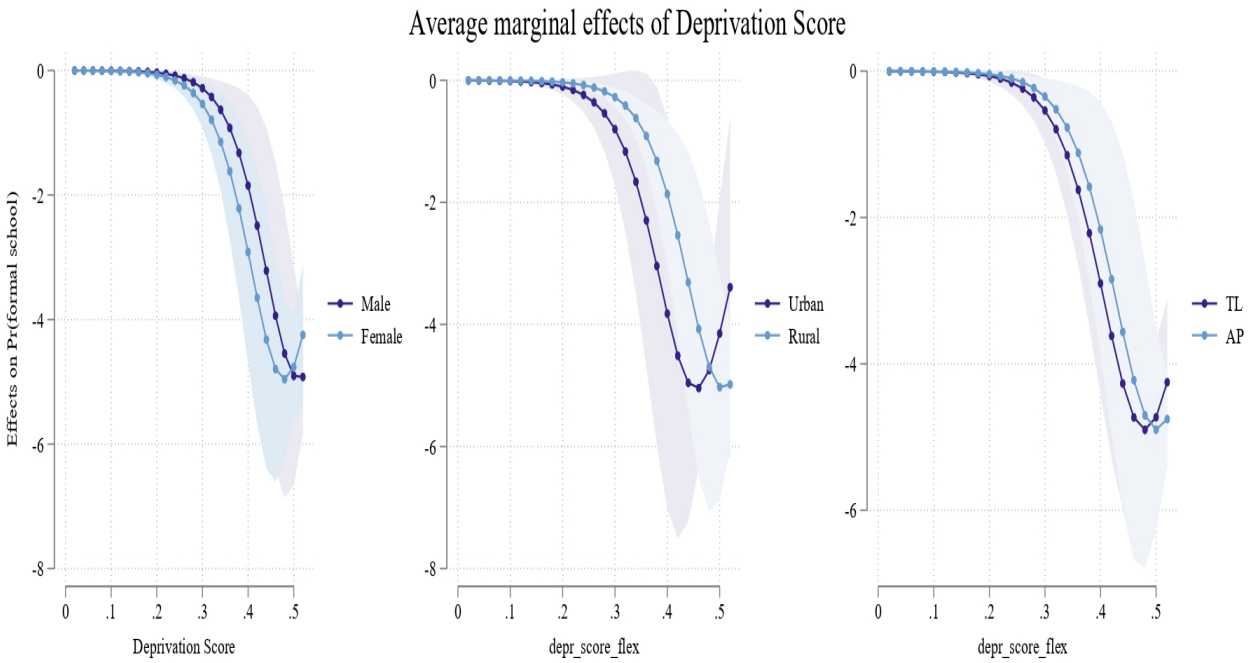


Figure 4: Average marginal effects of deprivation score on probability of formal school attendance across selected groups.

Supplementary Material for: Child Deprivation and Early Educational Outcomes: Evidence from Young Lives, India

February 23, 2026

1 Construction of Childhood Multidimensional Deprivation Index

This appendix documents the construction of the Childhood Multidimensional Deprivation Index (CMDI) used as the key explanatory variable in the main analysis. The index is constructed using data from the *Young Lives* longitudinal survey for India, drawing on Rounds 1–4 and focusing on early childhood outcomes. The purpose of this appendix is to ensure transparency and replicability of the index, while the broader conceptual motivation and normative discussion are developed in a companion paper.

Methodological Framework

The CMDI is constructed using the Alkire–Foster (AF) counting approach (Alkire and Foster, 2011), applied at the individual child level. This framework captures both the incidence and intensity of deprivation across multiple dimensions that are salient during early childhood.

Let the population consist of n children evaluated across d indicators spanning education, health, and living standards. Let x_{ij} denote the achievement of child i in indicator j, forming the achievement matrix $X = [x_{ij}]$. Each indicator is associated with a deprivation cutoff z_j. A child is considered deprived in indicator j if:

$$g_{ij} = \begin{cases} 1 & \text{if } x_{ij} < z_j \\ 0 & \text{otherwise} \end{cases}$$

The binary deprivation indicators form the deprivation matrix $G = [g_{ij}]$.

Dimensions, Indicators, and Deprivation Cutoffs

The index incorporates three core dimensions of childhood well-being: Education, Health, and Standard of Living. These dimensions are operationalized using 21 indicators drawn from the Young Lives survey,

selected to reflect age-appropriate deprivations and guided by international benchmarks (e.g., WHO and global MPI standards) as well as contextual relevance to India.

The Education dimension captures both household educational endowments and children's own access to early learning. Indicators include parental education (maternal and paternal) and age-appropriate measures of children's educational participation, such as preschool attendance and formal school enrollment.

The Health dimension covers antenatal, postnatal, and early childhood health conditions that are critical for survival and development. Indicators include antenatal care utilization, maternal nutrition and mental health, birth outcomes, breastfeeding practices, vaccination status, and child nutritional status.

The Standard of Living dimension reflects the household environment in which the child is raised, including housing quality, access to basic services, and economic security. Indicators capture housing materials, water and sanitation facilities, electricity access, cooking fuel, household congestion, and asset ownership.

A detailed list of indicators, their definitions, data sources, and deprivation cutoffs is provided in Figure-1.

Dimensions	Indicators	Sub-Indicators	Cohort (Round)	Cutoffs of Deprivation		Justification of Primary Cutoff
Education Dimension	Parental Education	Paternal Education	OC (R2), YC (R2)	Below Primary Education (< 6 years of Schooling)		The global MPI methodology (ISCED 1: Primary Education)
		Maternal Education	OC (R2), YC (R2)			
	Child's Educational Attainment	Pre-school Attendance	YC (R2)	0 = Child attended pre-school , 1 = otherwise		N.A.
		Formal School Attendance	OC (R1) , YC (R3)	0 = Child formal school, 1 = Child didn't formal school		
Health Dimension	Antenatal Care / Mother's Health	Number of antenatal visits	YC (R1)	Required number of antenatal visits is 3 (<=3)		State policy
		Mother received iron/folic acid during ANC	YC (R1)	0 = Mother received iron / folic tablets during ANC visits, 1 = Otherwise		N.A.
		Received tetanus injection	YC (R1)	0 = Mother received iron / folic tablets during ANC visits, 1 = Otherwise		
		Depression during antenatal care	YC (R1)	1 = Mother has depression during antenatal care, 0 = otherwise		
	Post - Natal Care / Child's Health	Child's Birth weight	YC (R1)	The ideal weight for child at birth is 2500 grams.		WHO recommendation
		Stunting	YC (R2)	0 = Child is not stunted, 1 = Child is stunted		N.A.
		Breast feeding	YC (R1)	Atleast 6 months of breastfeeding is necessary		WHO recommendation
		Full vaccination	YC (R1)	0 = If the child is fully vaccinated (BCG, Measles, Polio Vaccination), 1 = Otherwise		N.A.
				Deprived	**Not Deprived**	
Standard of Living Dimension	Housing	Floor material		Earthen Floor	Cement, Stone, Baked Clay, Laminated material and others	Contextualized following characteristics observed from sample region during field visit
		Roof material		Straw/Thatch, Earth/Mud, Wood/Planks, Others	Galvanised iron, Concrete/cement,	
		Wall material		Adobe/mud, Wood/branches, Galvanised iron, Matting,	Brick / Concrete Wall	
	Basic Services	Source of drinking water		Unprotected well, spring, pond, river, stream, other	Piped into dwelling/yard/plot, Tubewell in dwelling, Public standpipe/common, Tap/public well	
		Type of toilet facility		None, Other	Flush toilet/ Septic Tank in Dwelling, Pit latrine (Household's), Pit Latrine	
		Does dwelling have electricity?		0 = If the dwelling has electricity, 1 = Otherwise		
		Main fuel used for cooking		Wood, Charcoal, Coal, Cow Dung, Other	Kerosene / Paraffin, Gas / Electricity,	Contextualized characteristics observed from field visit
	Congestion	Household members per room		The number of persons per-room is the household is < 4.		Below average (2.93 ≈ 3)
	Asset Ownership	Assets		The household owns atleast one asset		The global MPI methodology

Figure 1: Dimensions (sub-dimensions) of childhood MPI estimation of the study based on Young Lives, India.

Weighting and Deprivation Scores

Indicators are equally weighted within each dimension, and dimensions are assigned equal weights, such that the sum of all indicator weights equals one: $\sum_{j=1}^{d} w_j = 1$. The weighted deprivation score for each child i is computed as:

$$c_i = \sum_{j=1}^{d} w_j g_{ij}$$

The score $c_i \in [0, 1]$ represents the share of weighted deprivations experienced by the child.

Poverty Cutoff and Identification

A multidimensional poverty cutoff $k \in (0, 1]$ is applied to identify deprived children. A child is classified as multidimensionally deprived if:

$$\rho_i(k) = \begin{cases} 1 & \text{if } c_i \geq k \\ 0 & \text{otherwise} \end{cases}$$

The main analysis adopts $k = 0.33$, consistent with standard MPI practice. Sensitivity to alternative cutoff values is examined as part of robustness checks.

Aggregation and Index Construction

The headcount ratio H, measuring the incidence of multidimensional deprivation, is defined as:

$$H = \frac{q}{n}$$

where $q = \sum_{i=1}^{n} \rho_i(k)$ denotes the number of deprived children. The average intensity of deprivation among deprived children is given by:

$$A = \frac{1}{q} \sum_{i=1}^{n} c_i \rho_i(k)$$

The Childhood Multidimensional Deprivation Index (CMDI), also referred to as the adjusted headcount ratio, is then computed as:

$$M_0 = H \times A$$

This measure jointly captures the prevalence and depth of deprivation.

Decomposability and Robustness

The AF measure satisfies dimensional decomposability, allowing overall deprivation to be expressed as the weighted sum of censored headcount ratios:

$$M_0 = \sum_{j=1}^{d} w_j h_j$$

where h_j denotes the proportion of children who are both multidimensionally deprived and deprived in indicator j.

Robustness checks explore alternative deprivation cutoffs for parental education, alternative weighting schemes across dimensions, and alternative poverty cutoffs. Results are shown to be qualitatively stable across these specifications.

Estimation and Data Handling

All indices are estimated using the `mpitb` package in Stata, accounting for survey weights and the complex sampling design of the Young Lives data. Children with missing information on any indicator are excluded from index construction. The CMDI is constructed as a time-varying measure across survey rounds, aligning deprivation exposure with subsequent educational outcomes analyzed in the main paper.

1.1 Distribution of Multidimensional Deprivation

Children experiencing higher levels of multidimensional deprivation are more likely to delay or forgo entry into formal schooling (Datta & Singh, 2016; Dutta, 2021; Kandapan, Pradhan, & Pradhan, 2023). Figure 3 presents the empirical distribution of multidimensional deprivation scores under strict and flexible definitions. The scores range from 0 (no deprivation) to 1 (maximum deprivation). The histogram and density plots show that both distributions are right-skewed. Under the flexible definition, a larger share of children fall within moderate deprivation levels, while the strict definition shifts the distribution toward higher scores, indicating more severe deprivation among those classified as deprived (Dutta, 2021). The cumulative distribution function (CDF) reinforces this contrast: cumulative probabilities rise more rapidly at lower deprivation thresholds under the flexible definition, consistent with polarization in deprivation intensity reported in related Indian studies (Mohanty, 2011; Kandapan et al., 2023).

Disaggregation by gender, region, sector, religion, caste, and intersecting identities reveals substantial variation in deprivation. Figure 4 indicates that female children experience higher deprivation across much of the middle range of the distribution under the flexible definition, suggesting moderate yet persistent gender disparities. Under the strict definition, the pattern becomes more polarized, with female children overrepresented at both ends of the distribution, highlighting continued heterogeneity in female welfare outcomes (Kandapan et al., 2023). Regional contrasts between Andhra Pradesh and Telangana

(Figure 5) reveal systematic disparities, aligning with broader evidence of inter-state inequalities in child deprivation across India (Dutta, 2021). Under the flexible definition, children in Telangana exhibit higher deprivation across the middle of the distribution, reflecting consistent disadvantages across multiple dimensions of well-being. Under the strict definition, disparities concentrate at the extremes, reflecting polarization between the least and most deprived children (Mohanty, 2011).

Sectoral differences are even more pronounced. Figure 6 shows that rural children face markedly higher levels of multidimensional deprivation under both definitions. The flexible specification highlights rural disadvantage among moderately deprived children, whereas the strict definition emphasizes severe deprivation concentrated among the most deprived group.Religious identity also shapes deprivation outcomes. Figures 7 and 8 show that Muslim children, followed by those belonging to Other Religions, experience systematically higher cumulative deprivation across most of the distribution compared to Hindu children, echoing broader evidence of religious disparities in child welfare (Kandapan et al., 2023). Under the flexible definition, Muslim children display broad-based deprivation across health, education, and living standards. Under the strict definition, the deprivation gap widens at the lower tail, reflecting a higher concentration of extreme deprivation among minority religious groups. Caste-based disparities remain deeply entrenched. As shown in Figures 9 and 10, children from Scheduled Castes (SC) and Scheduled Tribes (ST) exhibit upward-shifted cumulative distributions and dense clusters at the lower end of the probability density function, reflecting disproportionate representation among the most deprived. Under both definitions—though more pronounced under the strict specification—children from OBC and Other caste groups lie closer to the reference line, indicating relatively better outcomes (Dehury & Mohanty, 2017; Debata, Ranganath, & TS, 2023).

The intersection of religion and geography further amplifies inequality. Figure 11 shows that Muslim children in both Andhra Pradesh and Telangana experience consistently higher deprivation than Hindu children, with the disparity sharper in Telangana. Under the strict definition, the divergence is most pronounced at the lower tail, suggesting that deprivation among Muslim children is not only higher on average but also more intense among those already worst off. These group-level patterns align with the descriptive comparison of mean deprivation scores in Figure 2. Muslim children record the highest average deprivation, followed by those from ST and SC communities. Telangana exhibits higher mean deprivation than Andhra Pradesh, and rural children face greater deprivation than urban counterparts. Gender differences are smaller in magnitude but remain persistent, with female children showing slightly higher mean deprivation scores.

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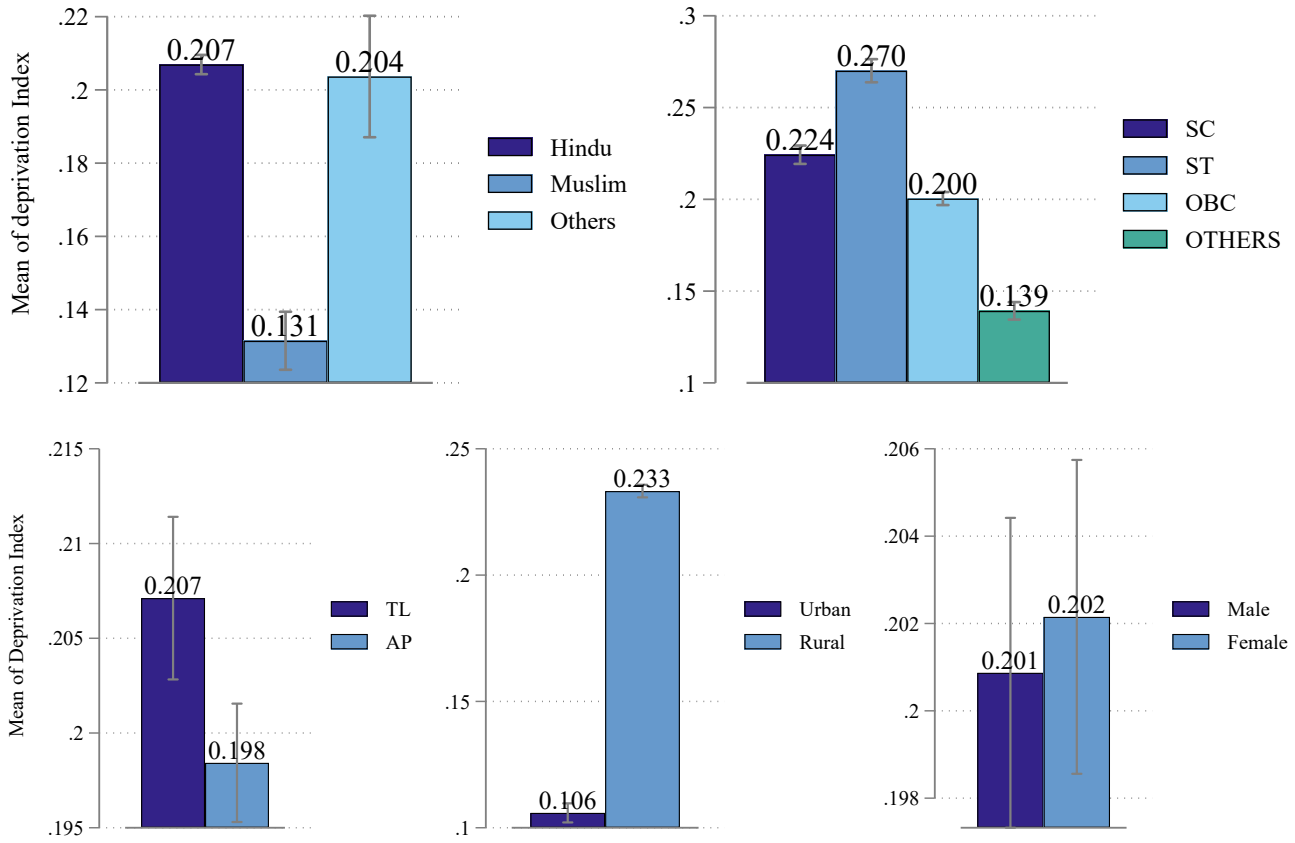


Figure 2: Mean multidimensional deprivation index across social and demographic groups.

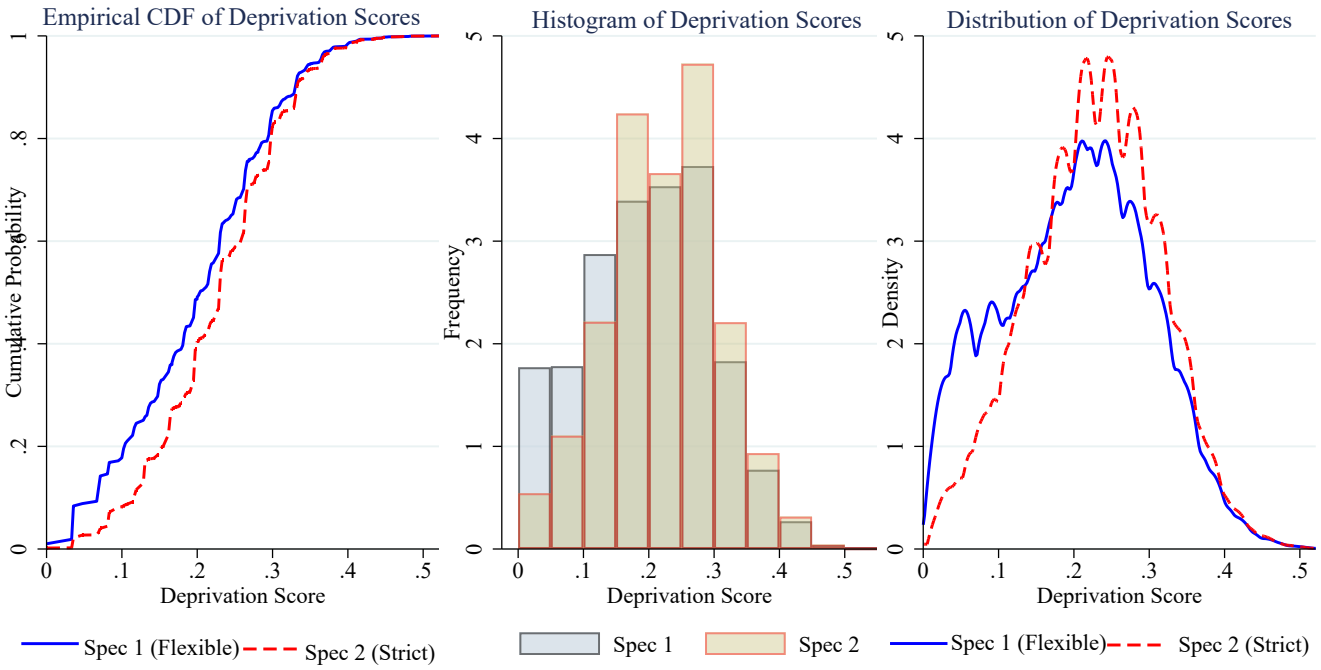


Figure 3: Distribution of Multidimensional Deprivation Scores.

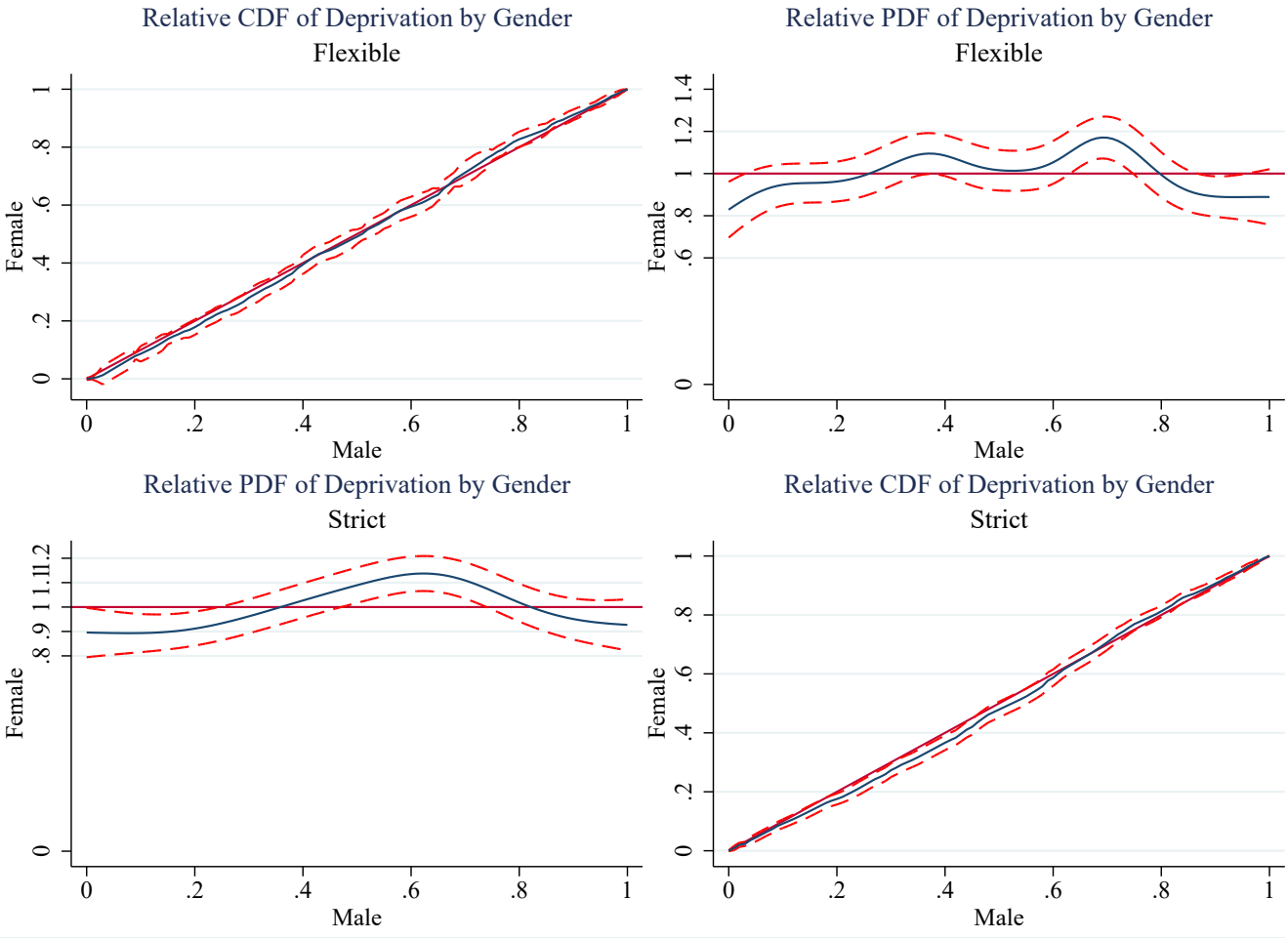


Figure 4: Relative distribution of CDF and PDF of deprivation score across gender.

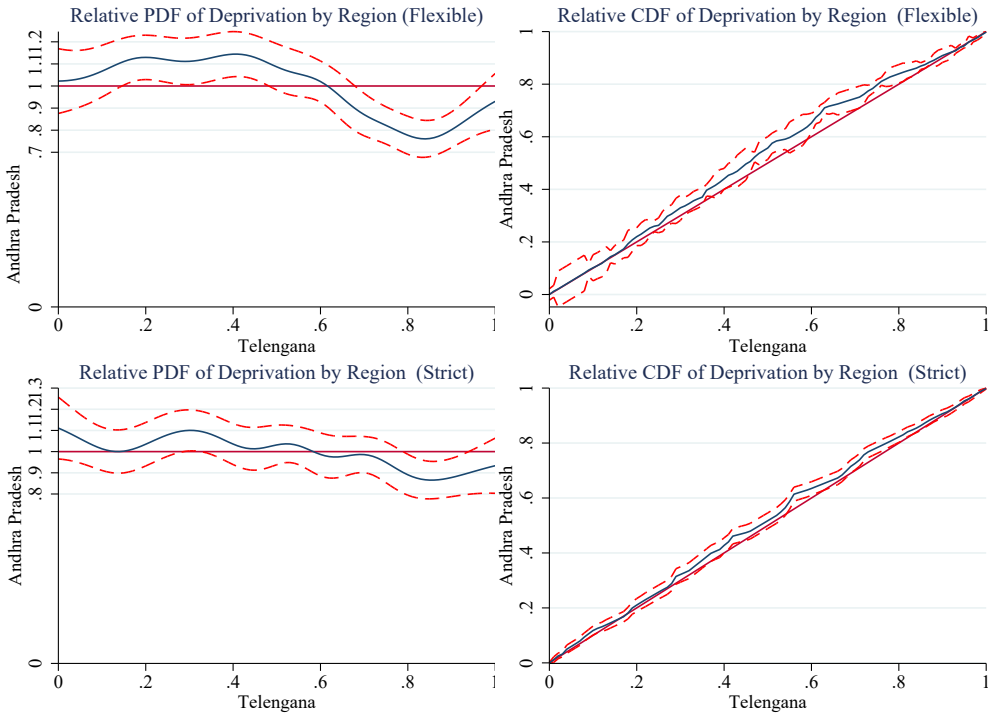


Figure 5: Relative distribution of childhood multidimensional deprivation scores across Andhra Pradesh and Telangana under strict and flexible definitions. Telangana shows broader mid-distribution disadvantage under the flexible definition and polarization at the extremes under the strict definition, indicating persistent regional disparities in childhood deprivation.

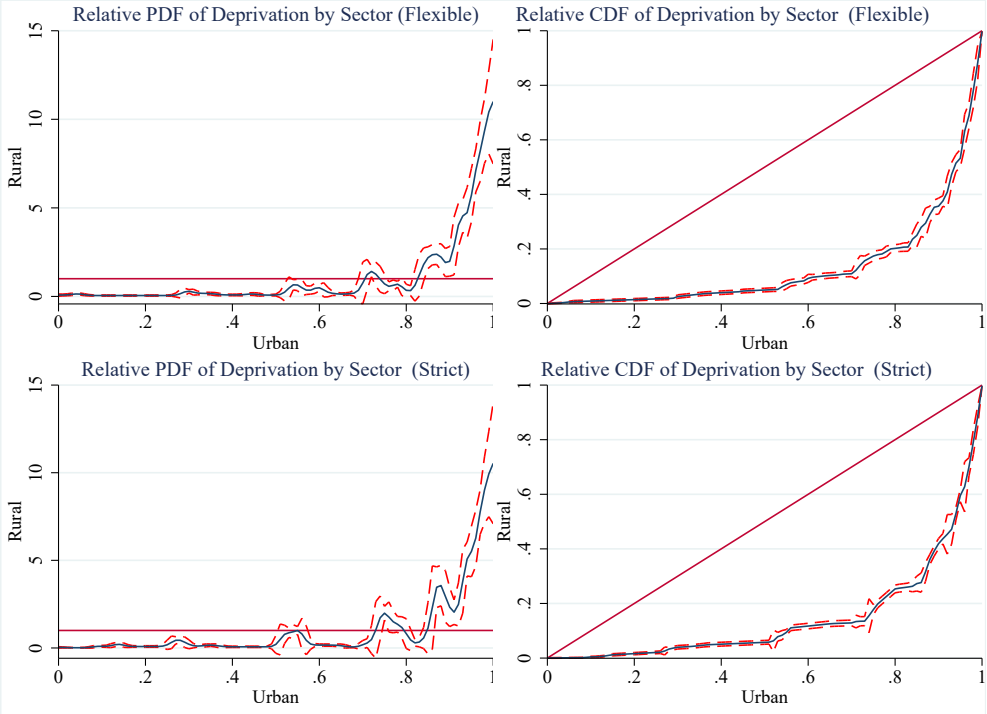


Figure 6: Relative distribution of childhood multidimensional deprivation scores across rural and urban sectors under strict and flexible definitions. Rural children exhibit consistently higher deprivation across the distribution, with clear stochastic dominance of rural curves, highlighting the persistence of structural rural disadvantage.

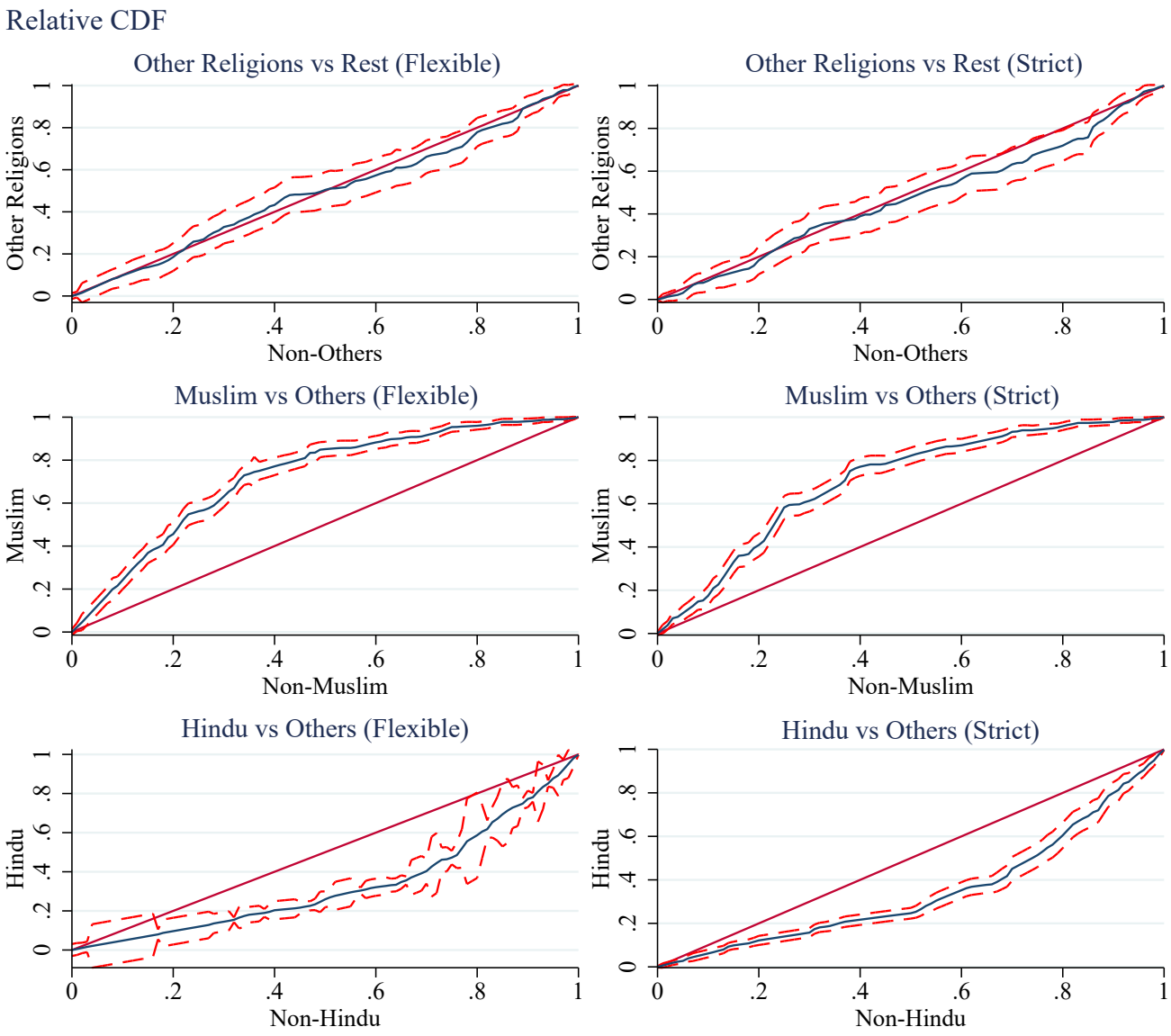


Figure 7: Relative distribution of CDF of deprivation score across religion.

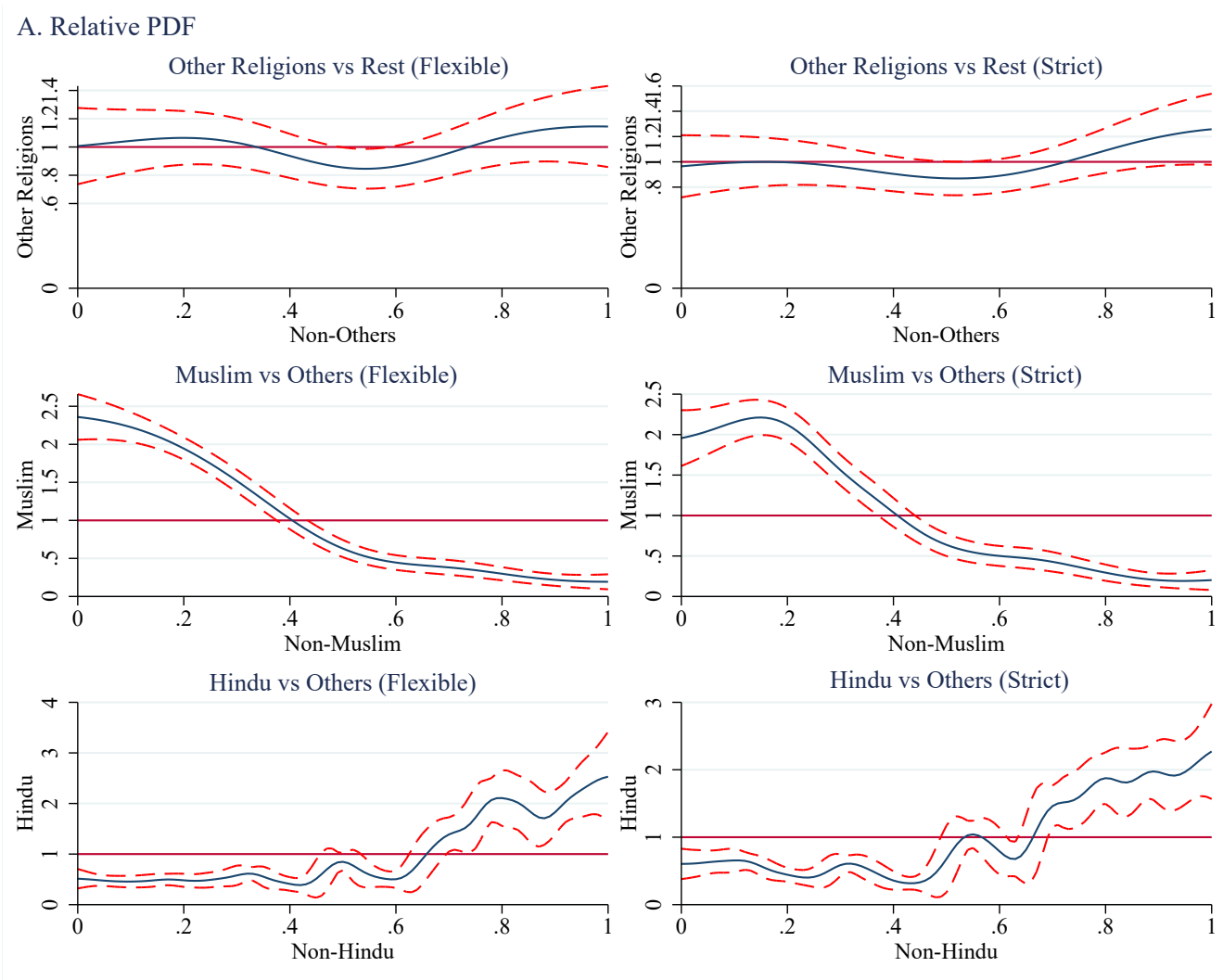


Figure 8: Relative distribution of PDF of deprivation score across religion.

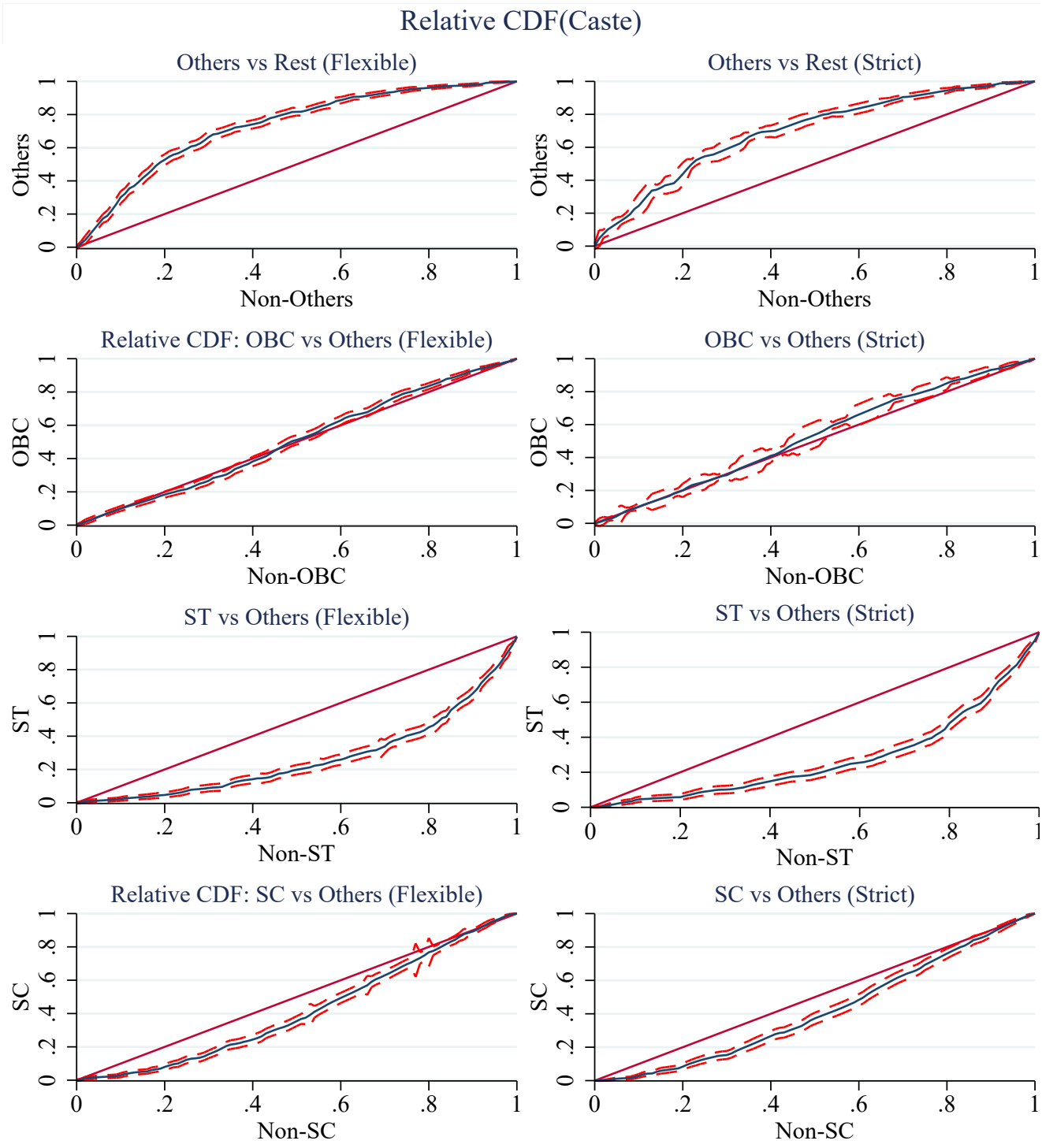


Figure 9: Relative distribution of CDF of deprivation score across caste.

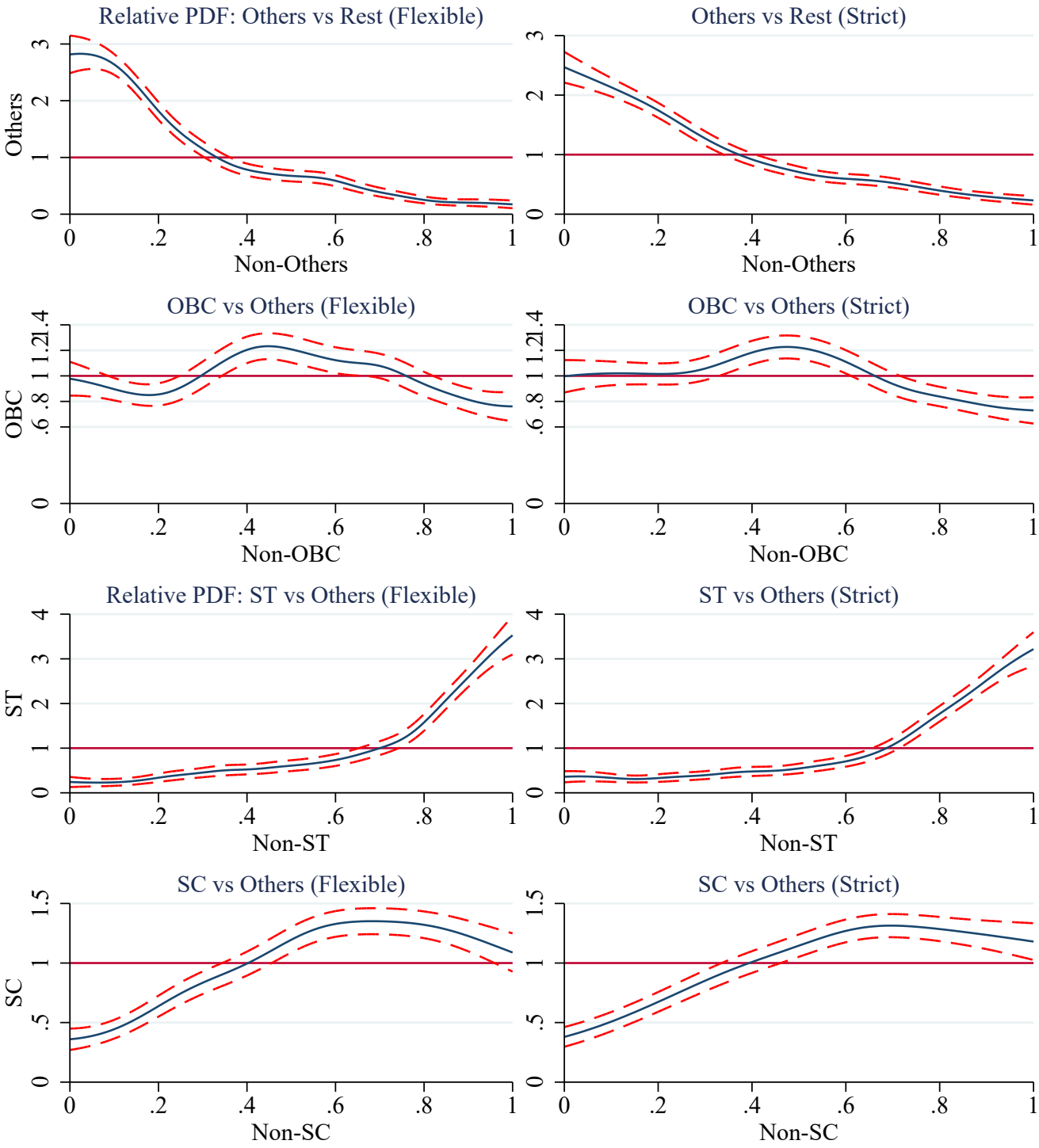


Figure 10: Relative distribution of PDF of deprivation score across caste.

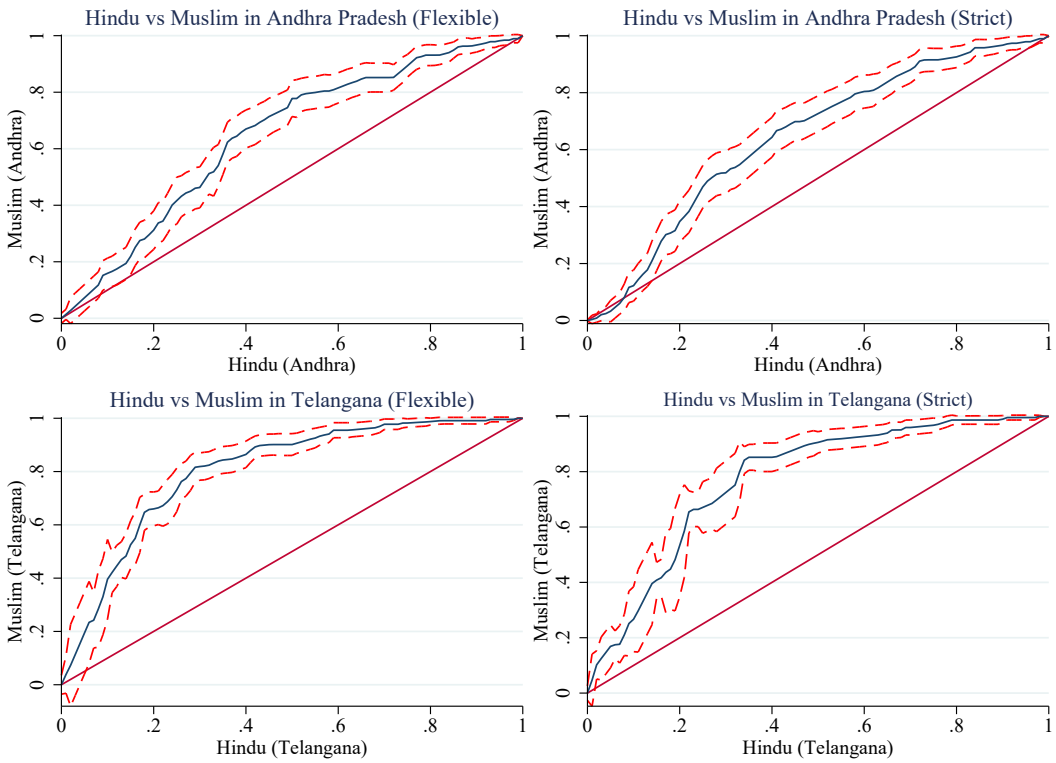


Figure 11: Relative distribution of PDF of deprivation score across religion and state.