Cover Letter

Ammazia Hanif
Institute of Economic Research, Hitotsubashi University
2-1 Naka, Kunitachi, Tokyo 186-8603, Japan
Ammaziahanif409@gmail.com; a262419c@r.hit-u.ac.jp
Homepage: https://amazia23.github.io/Amazia

Dear Professors Breza, Viviano, and Chandrasekhar,

I am writing to apply for the NBER Workshop on Network and Development Economics, to be held in Cambridge, Massachusetts, on December 5, 2026. I am currently an Adjunct Researcher and JSPS Research Fellow at the Institute of Economic Research, Hitotsubashi University, and an Adjunct Lecturer at Waseda University. I received my Ph.D. in International Public Policy (Economics) from the University of Tsukuba in 2025. My primary research interests are in development economics, health, and environmental economics, with a particular focus on health, human capital, and socioeconomic inequalities in developing countries.

My research examines how environmental conditions, community behavior, health constraints, and development interventions affect health and human capital in low- and middle-income countries. A recurring theme in my work is that individual outcomes can depend not only on household-level choices but also on conditions and behaviors in the surrounding community. For example, one of my working papers examines community-level sanitation externalities and shows that women remain exposed to the adverse health consequences of open defecation in their surrounding communities even when their own households have sanitation facilities. My ongoing collaborative work also includes a cluster-randomized child-nutrition intervention across 199 villages in Pakistan involving community health workers and technology-assisted communication. These projects have strengthened my interest in understanding community interactions, information transmission, and behavioral responses to development interventions. They have also motivated my interest in learning how empirical network methods can extend my current research by providing a more rigorous framework for studying social interactions, information diffusion, and spillovers.

For the workshop, I would like to present my working paper, "The Educational Toll of Anemia: Evidence from Adolescents in India." The paper examines whether adolescent anemia constrains educational participation in India, where a large out-of-school adolescent population coincides with a substantial and increasing burden of anemia. We construct a unique geographic panel dataset using multiple waves of the National Family Health Survey and estimate a fixed-effects instrumental-variable model, leveraging state-level beef-ban legislation and baseline cluster-level anemia prevalence to address the endogeneity of adolescent health. We find that anemia reduces the probability of school enrollment by 4.2 percentage points, with larger adverse effects among female and rural adolescents.

The NBER workshop would provide an invaluable opportunity to deepen my understanding of frontier empirical methods in network economics and to explore how these approaches can complement my current and future research. I would particularly value learning how network methods can be used to identify social interactions and spillovers, understand the diffusion of information and behavior, and improve the design and targeting of development interventions.

If I am shortlisted, the following faculty member can provide a recommendation:
Professor Takashi Kurosaki
Hitotsubashi University
Email: t.kurosaki@r.hit-u.ac.jp

Thank you very much for considering my application. I would be grateful for the opportunity to present my research, learn from the workshop faculty and participants, and develop new directions connecting health, human capital, and empirical network research in development economics.

Sincerely,

Ammazia Hanif

Motivation for Attending the NBER Workshop on Network and Development Economics

My research lies at the intersection of development economics, health economics, and environmental economics. I am particularly interested in understanding how health and environmental constraints affect human capital and socioeconomic outcomes, why these effects differ across vulnerable populations, and how public interventions can mitigate them. Methodologically, my research combines applied microeconometrics and causal inference with large-scale household surveys, geospatial data, panel data, and field experiments.

One strand of my research examines environmental and community-level determinants of health. My work on drinking-water contamination in Pakistan and community sanitation in Sub-Saharan Africa studies how environmental health risks affect children's and women's health and highlights the importance of conditions beyond the individual household. My broader research examines healthcare delivery and health-seeking behavior, including primary healthcare capacity and provider–patient matching in Cambodia, as well as the design and scalability of community-health-worker-based child nutrition interventions in rural Pakistan. A second strand investigates how health and household vulnerabilities translate into socioeconomic outcomes. My current work in India examines the effects of anemia on adolescents' educational participation and adults' employment and occupational sorting, while related research in Pakistan studies the intergenerational educational consequences of maternal exposure to violence. Together, these projects reflect my broader interest in how health, healthcare systems, community environments, and household vulnerabilities shape human-capital accumulation and economic opportunity in developing countries.

An important insight emerging from my research is that individual outcomes can also be shaped by the broader communities where people live. For example, my research on sanitation in Sub-Saharan Africa identifies health externalities from community sanitation conditions even among households having own toilet facilities. This has raised broader questions about how interactions among individuals and households influence health behaviors, and responses to development interventions. While my current work primarily captures these relationships through geographic and community-level measures, I am interested in learning how empirical network approaches can complement these methods by providing a more precise understanding of social interactions, information diffusion, and spillovers.

The NBER Workshop on Network and Development Economics would provide an ideal opportunity to develop this dimension of my research and broaden my empirical perspective. I am particularly interested in learning how network economics can help explain how information and behaviors spread within communities, distinguish social interactions from shared local conditions, and inform the design and targeting of development interventions. The workshop's focus on frontier empirical network research is especially relevant to my work because several of my projects identify community-level externalities and heterogeneous responses to health and development interventions without directly observing the social connections through which such effects may operate. Learning from recent advances in network methods would help me think more carefully about these mechanisms and assess how network-based approaches could be incorporated into future extensions of my research.

I am also strongly motivated by the workshop's combination of lectures by senior researchers and presentations of work in progress by early-career participants. At this stage of my career, I would greatly value the opportunity to discuss my ongoing research with scholars working at the frontier of development economics and receive constructive feedback on my research questions, empirical strategies, and interpretation of results. I am particularly interested in learning how other researchers translate network concepts into empirically tractable research designs in low- and middle-income settings. Such interactions would help me refine my current work and identify new methodological and substantive directions connecting health, human capital, social interactions, and development.

Finally, I look forward to the opportunity for intellectual exchange with other early-career researchers. Discussing common empirical challenges, exchanging ideas about data and methods, and learning from participants working on related development questions would broaden my perspective and may generate opportunities for future collaboration. I view participation in the workshop not only as an opportunity to deepen my understanding of empirical network research, but also to receive feedback on my work, develop new research ideas, broaden my academic network, and become more actively engaged with the international development economics research community.

Ammazia Hanif

Hitotsubashi University,
Institute of Economic Research (IER)
2 - 1 Naka, Kunitachi, Tokyo 68-8603, Japan
Tokyo, Japan

Email: Ammaziahanif409@gmail.com
Email: a262419c@r.hit-u.ac.jp
Homepage: https://amazia23.github.io/Amazia

Fields of Interest

Health Economics, Development Economics, Environmental Economics

Current Position

Adjunct Researcher Institute of Economic Research (IER) | JSPS Research Fellow IER, Hitotsubashi University | Adjunct Lecturer, Waseda University

Education

Ph.D. International Public Policy, University of Tsukuba, 2025 (major Economics)
Master of International Public Policy, University of Tsukuba, 2022 (major Economics)
Masters in Business Administration (MBA), University of Central Punjab, Pakistan, 2007

Previous Employment

Assistant Director/Planning Officer, Planning & Development Board, Government of Punjab, Pakistan (June 2015 – March 2025)
Customer Services Operations Manager, United Bank Limited, Punjab, Pakistan (Sep 2007–Jan 2012)

Research

Refereed Publication

The Benefit of Clean Water on Child Health: An Empirical Analysis with Specific Reference to *Escherichia Coli* Water Contamination (with Yuko Nakano and Midori Matsushima). ***Water Resources and Economics***. doi.org/10.1016/j.wre.2024.100249

Working Papers

Impact of Access to Improved Sanitation on Child Health in Pakistan.(with Yuko Nakano, Midori Matsushima). Tsukuba Economic Working Paper No.2022-003. https://pepp.hass.tsukuba.ac.jp/RePEc/2022-003.pd. Abstract *(under review)*

Educational Toll of Anemia: Evidence from Adolescents in India (with Takashi Kurosaki).Abstract *(under review)*

Effects of Community-level Sanitation on Women Anaemia: Evidence from Sub-Saharan Africa. ***Job Market Paper***(with Yuko Nakano and Midori Matsushima).Abstract *(under review)*

Effects of Trust & Interaction with doctors on online healthcare information seeking (HISI) in 25 countries (with Hamza Umer, Muhammad Salar Khan).*(under review).*

Capacity of Commune Health Centers to Provide Primary Healthcare Services under Post-COVID-19 in Phnom Penh, Cambodia 2023-24.(PIs: Hiroyuki Yamada, Midori Matsushima).A manuscript titled "Behavioral Preferences, Provider-Patient Matching, and Infant Survival: Evidence from Cambodia(with Midori Matsushima and Shusaku Sasaki)" is currently *(Under review)*. Abstract

Health, Employment, and Occupational Sorting: Gendered Labor Market Effects of Anemia in India (with Takashi Kurosaki)

Gendered Effects of Maternal Exposure to Violence on Children's Educational Attainment in Pakistan(with Hamza Umer and Takashi Kurosaki).

Work in Progress Research Projects and Activities (selected)

Economics of NGO-Academia Collaboration in Africa: Toilet Project in Madagascar 2022-2025.(PIs: Hiroyuki Yamada; Midori Matsushima). I contributed to questionnaire development, project field visit for a follow-up survey in 2023, and organized the data for the 2022-2024 rounds. Formal analysis is being conducted after generation of panel data.

Optimizing community-health-worker resources to scale child nutrition programs in Rural Pakistan(PIs: Abu S. Shonchoy, Takashi Kurosaki, Uzma Afzal, Agha Ali Akram, Akib Khan). The project is conducted in 199 villages of Sindh Province, using a Home-Based Growth Monitoring intervention to cope with child stunting. As a co-researcher, I have led the organization of all survey rounds, conducted the formal data analysis, and contributed to the manuscript preparation.

Locality-level sanitation behaviour and child health in developing countries (Ammazia Hanif).

Climate stress and women's health in developing countries (Ammazia Hanif).

Presentations (*(including scheduled*)

2026: 39th Japanese Association for South Asian Studies conference(20 September); Advances with Field Experiments Conference, University of Chicago (17 September); JEMIOW x J-TREE Workshop, GRIPS (11 July); 60th CEA (Canadian Economic Association) Conference (virtual) (22 May); Asia Meeting of the Econometric Society (AMES-23-25 January), NYU Abu Dhabi.
2025: 7th JADE (Japan Association for Development Economics)conference, JSPS -16th Hope meeting with Nobel Laureates, HIAS-GLECS seminar,Hitotsubashi University, EDW Seminar,IER (Institute of Economic Resaerch),Hitotsubashi University, ABEF x JTREE Joint workshop,GRIPS, Seminar JADE x JTREE July, 2025
2024: AERE@OSWEET(Association of Environmental and Resource Economists)(virtual), JSPS DC meeting at Kyoto International Conference Center, AFES (Africa meeting of econometric society) conference (virtual), JEA (Japanese Economics Association) Spring meeting, 58th CEA Conference (virtual), JADE x JTREE Joint workshop,GRIPS, PEPP (Program in Economics and Public Policy) special seminar,University of Tsukuba
2023: JEA Spring meeting, 57th CEA conference, Asian Economic Development Conference 2023, SWET workshop, Otaru, 18th JHEA (Japan Health Economic Association) Conference, Seminar on Water Economics OLLine (SWELL series).
2022: Young JADE Conference, Waseda University

Research and Teaching Experience (Japan)

Adjunct Lecturer (Part time), Development Economics-II, Waseda University (Fall, 2025- present).
Teaching Assistant for Globalization and Introduction to Microeconomics, University of Tsukuba (2022–2023).
Teaching Assistant for Data Science and Introduction to Geographic Information Systems (GIS), University of Tsukuba (2024–2025).
Subject Teacher Economics. Liberty International School, Tsukuba (Sep 2021- Mar 2022).
Research Assistant, University of Tsukuba for the project "Capacity of Commune Health Centers to Provide Primary Healthcare Services under Post-COVID-19 in Phnom Penh, Cambodia" (2024).
Research Assistant, University of Tsukuba for the project "Economics of NGO-Academia Collaboration in Africa: Toilet Project in Madagascar", (2022-2025).
Research Assistant for development projects at the Japan International Research Center for Agricultural Science (JIRCAS), Tsukuba (2022-2024).

Research Assistant, Ritsumaiken University for the project "Impact Evaluation of Violence Act on Women's Attitude Towards Violence in Pakistan" (2022-2023).

Awards, Honors, Grants, and Fellowships

Grants-in-Aid for Scientific Research (KAKENHI), Early-Career Scientists, JSPS, JPY 3.9 million, 2026–2029,(PI)
Grants-in-Aid for Scientific Research (KAKENHI)(C), 2026–2029, (Co-Investigator)
Project Research Program, Institute of Economic Research, Hitotsubashi University,2025-2026 (Co-PI)(JPY 0.5 million)
JSPS (Japan Society of Promotion of Science) Postdoctoral Fellowship (PD), Special Researcher 2025-2026.
Campus Ambassador, of Hitotsubashi University(2025-2026), Pakistan Students Association Japan (PSAJ).
Certificate of Commendation (role model student), International Public Policy, University of Tsukuba 2025.
JSPS HOPE Fellow, 16th HOPE MEETING with Nobel Laureates,Japan, March 9-13, 2025.
JSPS Doctoral candidate (DC2) Special Researcher, 2024-2025.
Travel Grant to present research results at the SWET workshop, Otaru, Hokkaido,2023.
TOEIC (Score 795, 2023) – International English communication certification.
Kubota Fund Scholarship, 2023-2024.
Tsukuba Scholarship, 2022-2023.
Joint Japan World Bank Scholarship (JJWBSP), 2020-2022.
Outstanding Master's Thesis Award (1st place), PEPP program, University of Tsukuba, 2022.
JICA-IUJ Program -Understanding Japanese Development Experience, 2022.
21-day Bilateral Seminar on the Development of Economic Zones in Pakistan, in China, 2018.

Project Field Visit

Project field visit to Madagascar (May 2023) for project "Economics of NGO-Academia Collaboration in Africa: Toilet Project in Madagascar, 2022-2025.(PIs: Hiroyuki Yamada; Midori Matsushima).

Refereeing

Water Resources and Economics, Nature-Humanities and Social Sciences Communications, Frontiers in Public Health, Journal of Social and Economic Development.

Softwares and Other Skills

Stata, QGIS, R (intermediate), LaTeX, Google Earth Engine (beginner). ***Language***: English(fluent), Japanese(basic), Urdu(native), Arabic(basic)

References

Takashi Kurosaki
Professor (Economics)
Institute of Economic Research
Hitotsubashi University
t.kurosaki@r.hit-u.ac.jp

Yuko Nakano
Professor (Economics)
Program in Economics and Public Policy
University of Tsukuba
ynakanoyuko@gmail.com

Abu S. Shonchoy
Associate professor of Economics
Florida International University (FIU)
Miami, USA parves.shonchoy@gmail.com
pshonchoy@fiu.edu

Midori Matsushima
Associate professor (Economics)
Program in Economics and Public Policy
University of Tsukuba
matsushima.midori.gb@u.tsukuba.ac.jp

Uzma Afzal
Assistant professor (Economics)
School of Economics, Finance and Marketing at RMIT, Australia
uzma.afzal@rmit.edu.au

Master’s Program in International Public Policy (Economics)

No.202103329.

UNIVERSITY OF TSUKUBA
Tsukuba Ibaraki 305-8577, Japan

CERTIFICATE

Record of Ammazia Hanif
Date of Birth: January 23, 1982
Student ID No: 202026014
Program: Degree Programs in Humanities and Social Sciences, Graduate School of Business Sciences, Humanities and Social Sciences
Master's Program in International Public Policy
Years Attended: From October 1, 2020 to March 25, 2022
Degree Received: Master of Arts in International Public Policy

Year	Subject	Credit	Grade
2020	Academic Writing and Research Ethics	1.0	A
2020	Japan's Politics and Civil Society 1	1.0	A
2020	Intermediate Microeconomics	2.0	A
2020	Data Management	1.0	A+
2020	Advanced Data Management	1.0	A
2020	Econometrics I	1.0	A
2020	Seminar on Economics I	1.0	A+
2020	Academic Writing for Graduate Students	2.0	A+
2020	The Fundamentals of Public Policy and Management	2.0	A+
2020	Geographic Information System and Satellite Data Analysis for Economists	2.0	A+
2020	Joint Seminar for Master's Thesis	1.0	A
2020	Social Development	1.0	A
2020	Seminar on Policy Analysis and Programme Evaluation A	1.0	B
2020	Intro-Intermediate Macroeconomics	2.0	A+
2020	Statistics	2.0	A+
2021	International Finance and Policy	2.0	A+
2021	Economics of Development	1.0	A+
2021	Microeconomics	2.0	A+
2021	Seminar on Economics II	1.0	A+
2021	Seminar on Economics III	1.0	A+
2021	Public Economics	2.0	A+
2021	Global Issues and Global Society: Environmental Pollution and Health Effects	1.0	A
2021	Econometrics II	1.0	B
2021	Research Workshop on International Public Policy A	3.0	A+
2021	Research Workshop on International Public Policy B	3.0	A+
2021	Seminar on Middle East and North African Studies BII	1.0	A
	[Total Credits]	39.0	

Grading System until Academic Year 2012 : A(100-80), B(79-70), C(69-60), P(Passing), T(Transferred from other institution).
Grading System from Academic Year 2013 : A+(100-90), A(89-80), B(79-70), C(69-60), P(Passing), T(Transferred from other institution).

Date: March 25, 2022

Official Seal

Signature:

NAGATA Kyosuke
President,
University of Tsukuba

Ph.D. Transcript

No.202403265.

UNIVERSITY OF TSUKUBA
Tsukuba Ibaraki 305-8577, Japan

CERTIFICATE

Record of Ammazia Hanif
Date of Birth: January 23, 1982
Student ID No: 202230029
Program: Degree Programs in Humanities and Social Sciences, Graduate School of Business Sciences, Humanities and Social Sciences
Doctoral Program in International Public Policy
Years Attended: From April 1, 2022 to March 25, 2025
Degree Received: Doctor of Philosophy in International Public Policy

Year	Subject	Credit	Grade
2022	Special Seminar on Policy Analysis and Programme Evaluation AII	1.0	A+
2022	Special Seminar on Economics AI	1.0	A
2022	Special Seminar on Economics AII	1.0	A
2023	Special Seminar on Policy Analysis and Programme Evaluation BI	1.0	A+
2023	Special Seminar on Policy Analysis and Programme Evaluation BII	1.0	A+
2023	Special Seminar on Economics BI	1.0	A
2023	Special Seminar on Economics BII	1.0	A
2024	Applied Time Series Analysis	2.0	B
2024	Seminar on International Public Policy Project A	3.0	A+
2024	Seminar on International Public Policy Project B	3.0	A+
2024	Special Seminar on Policy Analysis and Programme Evaluation AI	1.0	A+
	[Total Credits]	16.0	

Grading System until Academic Year 2012 : A(100-80), B(79-70), C(69-60), P(Passing), T(Transferred from other institution).
Grading System from Academic Year 2013 : A+(100-90), A(89-80), B(79-70), C(69-60), P(Passing), T(Transferred from other institution).

Date: March 25, 2025

Official Seal

Signature: _____

NAGATA Kyosuke
President,
University of Tsukuba

The Educational Toll of Anemia: Evidence from Adolescents in India

Ammazia Hanif* [1] Takashi Kurosaki [2]

[1] Institute of Economic Research, Hitotsubashi University, Tokyo, Japan

[2] Institute of Economic Research, Hitotsubashi University, Tokyo, Japan

Abstract

A significant number of out-of-school adolescents and the increasing anemia prevalence pose a critical barrier to human capital development. We assess the impact of adolescent anemia on school enrollment in India by constructing a geographic panel dataset using National Family Health Survey waves. We estimate a fixed-effects instrumental variable model, leveraging the state-level beef ban legislation and baseline cluster-level anemia prevalence to generate our instruments. We find that anemia reduces the likelihood of school enrollment by 4.2 percentage points. This effect is more pronounced among female adolescents, those from rural areas, and those residing in states with lower implementation of the national anti-anemia policy. Moreover, the effect is less pronounced for adolescents who are the children of the household head than for those who are not. Overall, the findings highlight the critical role of adolescent health, particularly anemia, in shaping educational participation and underscore the significance of targeted public health interventions to address structural health disparities.

JEL classification: I15, I18, I25, I12, O15

Keywords: Adolescent anemia, hemoglobin, school participation, beef ban, anti-anemia program, India

* Email address: ammaziahanif409@gmail.com. The authors appreciate the valuable comments from the participants at the Economic Development Workshop (EDW), Hitotsubashi University. The paper is scheduled to be presented at the 60th Canadian Economic Association, May 2026 and 39th Annual Conference of Japanese Association of South Asian Studies, September 2026. The authors would like to acknowledge the DHS program for providing open access to its datasets. A.H. gratefully appreciates the financial support from the JSPS.

1. Introduction

Across the globe, about 272 million children and adolescents of primary and secondary school age were not attending school in 2023, and the evidence suggests that out-of-school rates, particularly at the upper secondary level, are on the rise (UNESCO, 2025). The United Nations' Sustainable Development Goals (SDGs) call for universal completion of primary and secondary education by 2030. While primary school enrollment has nearly reached universality, secondary school participation remains substantially low, particularly in low- and middle-income countries (LMICs) (De Neive et al.,2024; Local Burden of Disease Educational Attainment Collaborators, 2020). India, which has the world's largest adolescent population with over 250 million (Anand et al., 2014), faces a particularly severe challenge. Over 52 million adolescents of secondary school age were out of school in the country, the highest number globally (UNESCO, 2024).

Despite their significance as determining factors of human capital development, micronutrient deficiencies, particularly anemia, remain widespread across various LMICs. Such deficiencies can be a potential contributor to nutrition-based poverty traps (Dasgupta and Ray, 1986)[1], as they may constrain educational attainment and influence human capital development (Chong et al., 2016; De Neve et al., 2024). Anemia affects nearly one-third of the global population (Chaparro & Suchdev, 2019). The economic implications of anemia, particularly iron deficiency anemia (IDA)[2], are enormous, as it can cause fatigue, developmental delays, reduce physical and cognitive capacities, lower attention span and

[1] Chong et al., (2016) note that although proving a nutrition-based poverty trap is difficult, exploring whether reduction in iron deficiency anemia causally improves human capital can reveal its potential in sustaining intergenerational poverty.

[2] Iron is essential for central nervous system and brain, as it supports enzyme driven processes such as neurotransmitter synthesis, neurotransmitter catabolism, and myelin production vital for neural health.

work capacity, and elevated infection risks (Grantham-McGregor & Ani, 2001; Haas & Brownlie, 2001; Kinyoki et al., 2021; More et al., 2013). These physiological impairments can potentially influence the adolescent's cognitive performance and hinder their ability to sustain regular school attendance. Prior research suggests that IDA has been observed as one of the determinants of schooling outcomes (Chong et al., 2016).

India represents a particularly compelling case. It ranks amongst the countries with the highest anemia prevalence globally (Stevens et al., 2013), and the situation has aggravated in recent years among all populations, specifically anemia prevalence among adolescents increased from 54% to 58.9% from 2015 to 2021 (Chakrabarty et al., 2023). At the same time, India has the largest out-of-school adolescents worldwide. This dual burden underscores the need for a rigorous, large-scale empirical investigation into whether adolescent anemia directly affects school participation.

Prior research on anemia, iron deficiency, and schooling outcomes has yielded mixed results. Some found that reducing iron deficiency and anemia significantly improves adolescents' schooling attainment and learning outcomes (Nguyen et al., 2022; Chong et al., 2016), while others documented positive effects of improving iron status on school participation among younger children (Bobonis et al., 2006), and an increase in hemoglobin concentration was correlated with higher intelligence quotient scores (Ezzati et al., 2004). Research also displayed that children and adolescents with iron deficiency, particularly those who were anemic, performed worse in cognitive tests (More et al., 2013; Halterman et al., 2001). Conversely, recent evidence suggested no significant relationship between adolescent anemia and school attendance (De Neve et al., 2024). Prior research, however, has not sufficiently addressed potential endogeneity and confounding factors in estimating the effect of adolescent anemia on school attendance.

We study the effect of anemia on school enrollment among adolescents in India by using the National Family Health Survey (NFHS) data. We use two NFHS rounds—NFHS-4 (2015-16) and NFHS-5 (2019-21) to construct a geographic panel dataset. Since NFHS is cross-sectional in nature, we use the geocoded positions of clusters from both waves to match the nearest clusters within a 10-kilometer (km) distance radius and construct a "geographic panel dataset". To investigate how individual anemia influences school enrollment, several factors demand consideration. The anemia prevalence within a locality can be endogenous owing to several unobserved factors that also affect the individual's school participation. Additionally, reverse causality may arise if school attendance influences nutritional intake through school-based micronutrient supplements, thereby affecting anemia.

To address these potential concerns, this study uses a fixed effects instrumental variable (FE-IV) approach with two novel instruments and an extensive control set. The first is the interaction term between the state-level possession or sale of the beef ban and the beef-consuming group, and a post-period time dummy. This IV captures the variation in anemia driven by beef bans, which were politically motivated and disproportionally effected certain dietary communities, reducing their hemoglobin levels (Dasgupta et al., 2023). These bans reduce access to one of the most affordable sources of dietary iron and animal protein for groups that traditionally consume beef more than those who do not[3]. Additionally, during the study window, a nationwide health program, Anemia Mukt Bharat (AMB), was launched in India. This program follows a "6×6×6 strategy": six beneficiary groups, six programmatic interventions, and six institutional mechanisms, and is found to be effective in reducing the issue of anemia through multiple interventions (Joe et al., 2022). We expect that a cluster

[3] To generate state-level beef ban status, we use the information compiled by Dasgupta et al. (2023).

with higher initial anemia prevalence underwent greater improvement in hemoglobin levels in the following years, and we observe a negative association between baseline cluster anemia prevalence and subsequent reductions in anemia. We exploit this variation in baseline cluster-level anemia prevalence and the subsequent changes and employ the cluster's initial anemia prevalence rate interacted with post-intervention time dummy as an IV for adolescent anemia.

Our findings show that adolescent anemia reduces the likelihood of school enrollment by 4.2 percentage points. We also examine heterogeneities in this effect. First, the negative effect is significant and stronger among girls than boys, possibly due to the lower prevalence and variability of anemia among boys, their lower likelihood of school withdrawal given the higher perceived returns to education, and greater parental investments in sons. Second, analysis of adolescents' relationships to the household head indicates that the effect of anemia is less pronounced for adolescents who are the children of the household head compared to those who are not, possibly due to the differences in intra-household resource allocation and caregiving priorities. Third, stratification by household location reveals that anemia has a significant and negative effect on school enrollment in rural areas, potentially due to limited access to healthcare services, lower awareness, and weaker institutional support than in urban areas. Finally, analysis by state-level AMB index scores, depending on Iron and Folic Acid (IFA) supplementation coverage, indicates that the detrimental impact of anemia is larger and significant in states with lower index values than in states with higher values, suggesting that the effectiveness of the program in mitigating anemia's adverse impact varies with the intensity of IFA supplementation coverage. Overall, our findings highlight adolescent anemia as a binding constraint on human capital formation and provide suggestive evidence for targeted public health interventions.

Our paper contributes to several strands of literature. First, we provide large-scale empirical evidence on the effect of anemia on adolescents' school participation, adding to a limited but growing literature on adolescent anemia and educational outcomes. For instance, a recent related study by De Neve et al. (2024) found no statistical association between adolescent anemia and school attendance when using household fixed effects. While this design decreases bias from unobserved household-level factors, it also eliminates a significant meaningful variation by restricting the sample to households with more than one adolescent. Methodologically diverging from prior work, we employ the FE-IV approach to address potential endogeneity concerns. Specifically, we exploit geographic and policy variation as natural experiments by leveraging state-level beef ban legislation interacted with beef consumer communities and post-period dummy, and cluster-level initial anemia prevalence interacted with post-period dummy as instruments. This approach enables credible identification of the effect of anemia on school enrollment in a large-scale setting. To the best of our knowledge, this is the first study to provide large-scale empirical evidence on anemia and school enrollment by addressing endogeneity using novel instruments.

Second, our study speaks to research on the iron deficiency, schooling attainment, and cognitive function, encompassing both observational studies and randomized controlled trials (RCTs), that show improved iron status and hemoglobin levels through iron supplementation and deworming drugs improve intelligence quotient, cognitive function, and school performance and participation (e.g., Krämer et al., 2021a; Chong et al., 2016; Bobonis et al., 2006; Bleakley, 2007; Ezzati et al., 2004 ; Miguel & Kremer, 2004). However, Krämer et al. (2021b) found that reducing anemia through double fortified salt in school meals had no significant impact on school attendance, test scores, and cognitive performance of primary school children. While most prior work examining the link between iron deficiency, anemia,

and education has focused on younger children, we provide large-scale empirical evidence for adolescents, a group facing a highly prevalent yet treatable health challenge. Although some small-scale studies have linked adolescent anemia and learning outcomes and schooling attainment (Nguyen et al., 2022; Chong et al., 2016; More et al., 2013), with many focused primarily on girls (More et al., 2013), large-scale evidence focusing on both genders remains limited.

Third, our work relates to the broader health and human capital literature, which mainly suggests that negative health shocks in early life can have lasting effects on educational and labor market outcomes and skill development (Behrman, 1996; Currie, 2009). Drawing on their health-human capital framework and on RCT-based evidence from Peru estimating the causal effect of adolescent anemia on human capital attainment (Chong et al., 2016), we focus on adolescents in the Indian context to estimate the impact of anemia on school enrollment. Finally, the heterogeneity analyses by adolescents' gender, relationship to the household head, rural or urban residence, and AMB index fill an important gap. Since such subgroup analyses are scarce, this study adds value to the literature, and the findings can provide policy-relevant insights for targeted school retention and anemia reduction interventions.

The remainder of the paper is organized as follows. Section 2 describes the data sets utilized in the analysis. Section 3 outlines the empirical strategy and estimation methods. Section 4 presents the results, and Section 5 provides a conclusion.

2. Data

2.1 Data Formation and Sample

In this study, we utilize two rounds of nationally representative household surveys, i.e., NFHS-4 (2015-16) and NFHS-5 (2019-21) (IIPS and ICF, 2017; IIPS and ICF, 2021). Both rounds contain biomarker data on hemoglobin measurements, cluster-level identifiers with geocoded locations, and adolescents' schooling information. Since NFHS is not a panel data set, the inherent cross-sectional nature of NFHS prevents us from constructing a conventional panel dataset for the same clusters. Additionally, for anonymity, geo-masking of clusters is introduced by NFHS. To address this, we use a pair-matching strategy and match the nearest clusters in such a way that the shortest distance between the two NFHS clusters from both waves is within a 10-km radius and call it "geographic panel data" (Hanif, Nakano, and Matsushima, 2024). The basic assumption is that the clusters in similar locations are analogous in terms of socio-economic and health conditions. We harmonize this geographic panel data with individual-level NFHS data. We restrict our sample to adolescents aged 15–18 years because the NFHS records the hemoglobin concentration for individuals aged 15 and older, and the secondary school attendance de jure continues until about age 18. This results in 17,946 geographic sample localities, with 78,737 adolescents in 2015 and 70,628 adolescents in 2021. The total sample size is 149,365 individual adolescents, comprising 130,303 females and 19,062 males. As the NFHS systematically samples more females than males, because the survey primarily focuses on child and maternal health, the gender balance of our data is skewed towards females[4]. Later, we will test the robustness of our estimations

[4] In NFHS-4, 699,686 eligible women aged 15-49 years and 112,122 men aged 15-54 participated from 616,346 households and in NFHS-5, 747,176 women and 111,179 men participated from 636, 699 households.

and the likelihood of measurement error by employing different distance thresholds to construct geographic panel data. Fig. 1 visualizes the study clusters in India.

[Fig. 1]

2.2 Key outcome and explanatory variables

The main outcome variable is an adolescent's school enrollment status during the survey year, a binary indicator that takes 1 if the adolescent attended school or college during the NFHS survey year, and 0 otherwise[5]. The exposure variable is an adolescent anemia dummy, which equals 1 if the adolescent was suffering from anemia at the time of the survey, and 0 otherwise. Anemia is defined as a hemoglobin concentration below 11.9 g/dL for non-pregnant women, below 10.9 g/dL for pregnant women, and below 12.9 g/dL for men. In the NFHS, all eligible women aged 15–49 in the selected households were interviewed, whereas eligible men aged 15–54 were interviewed from a subsample of selected households about the household characteristics and their health experiences, and were tested to assess their blood hemoglobin concentration. Following WHO guidelines on hemoglobin cutoffs, we classify anemia in women as mild if the hemoglobin concentration is between 11.0 g/dL and 11.9 g/dL, between 8.0 g/dL and 10.9 g/dL as moderate anemia, and below 8.0 g/dL as severe anemia. Similarly, for men, anemia is defined as mild anemia having hemoglobin levels between 11.0 g/dL and 12.9 g/dL, between 8.0 g/dL and 10.9 g/dL as moderate anemia, and below 8.0 g/dL as severe anemia (WHO, 2024).

We will explain later that, in the model, we also incorporate pre-existing cluster-level anemia prevalence for the year 2010. We cannot extract this information from the previous

[5] We use the specific question from NFHS-4 and NFHS-5 "Did (NAME) attend school or college at any time during the survey school year?"

wave of NFHS-3 (2005), which does not provide geocoded information of clusters. To circumvent this, we use spatial raster data for anemia prevalence from the Institute for Health Metrics and Evaluation (IHME, 2021) and match it to sample NFHS clusters (see Section 4.3). Cluster-level precipitation and temperature data are extracted from the Climate Research Unit Time Series (CRU-TS) version 4.09, which offers historical monthly climate data at a spatial resolution of 0.5° × 0.5° grids (Harris et al., 2020).

Appendix Table A1 reports the key variable statistics stratified by the survey year. The data indicate that, on average, anemia prevalence increased by 7.8 percentage points between 2015 and 2021 within the sample clusters[6]. Supplementary Fig. S1 maps the state-level anemia prevalence among sample adolescents, indicating that the anemia prevalence increased in most of the states from 2015 to 2021. The data also depict that adolescents' school enrollment during the survey years increased from 67.8 percent to 70.1 percent. Around 61.0 percent of adolescents live in beef-ban states, and 40.0 percent belong to beef-consuming religious communities. In subsequent regression models, we control for a range of individual and household characteristics, including adolescents' gender, age, and body mass index (BMI); gender, religion, and educational attainment of the household head; household structure (nuclear or non-nuclear); and the area of residence. Household-level indicators include access to piped water, and internet to account for the household's socioeconomic status. Cluster-level variables include average temperature, average

[6] Our data indicates that average level of hemoglobin is 11.64 for girls, below the anemia threshold (12 g/dL) and the hemoglobin level for boys is 13.69, just above the threshold (13 g/dL), suggesting that the issue is severe particularly among females.

precipitation, and the proportion of households with access to piped water, Below Poverty Line (BPL) cards, and internet as continuous indicators.

2.3 Beef ban legislation

India provides a unique context for this study due to its high prevalence of anemia and the imposition of state-level beef ban laws. Previous research shows that beef bans significantly reduced hemoglobin levels among groups that traditionally consume beef compared to those who do not (Dasgupta et al., 2023). In this study, we draw on a rich database compiled by Dasgupta et al. (2023), which contains information on cattle slaughter regulations and bans on the possession or sale of beef across Indian states, as set by policy between 1950 and 2016, with no significant changes reported after that during our study period. Beef is considered a rich source of dietary iron and one of the cheapest forms of animal protein (Dasgupta et al., 2023; Ferry, 2020). In India, beef is generally cheaper than mutton, pork, or chicken and is among the most affordable sources of iron in the diet of minority communities that traditionally consume beef, such as Muslims, Scheduled Caste (SC) Hindus, and Christians. Thus, it is reasonable to assume that in states where beef ban laws were in place, individuals from beef-consuming groups experienced a reduction in access to beef. In contrast, most of the Indian ethnic and religious groups—Sikhs, Jains, non-SC Hindus, and Parsis that are traditionally prohibited from consuming beef may not be affected by these bans in their diets (see Supplementary Information for details).

In Fig. 2, we illustrate the implementation status of beef possession and/or sale bans across Indian states and Union Territories (UTs), drawing on Dasgupta et al. (2023). We use this variation in state-level possession or sale bans to construct our instrument for anemia prevalence.

[Fig. 2]

2.4 Anemia Mukt Bharat (AMB) Program

To examine the impact of anemia on school enrollment, we draw on NFHS data from 2015–16 and 2019–21, which span the pre and post–launch periods of the AMB program. This program, launched in 2018, is India's flagship national initiative to combat anemia. It follows a "6×6×6 strategy": six beneficiary groups, six programmatic interventions, and six institutional mechanisms to strengthen health systems (MoHFW, 2018). The six beneficiary groups comprise children (6-59 months), children (5-9 years), adolescents (10-19 years), lactating women, pregnant women, and women of reproductive age (15-49). The six interventions target both treatment and prevention of anemia, while the six institutional mechanisms aim to ensure effective implementation, and the program implementation intensity varies across states.

We use the AMB program in this study in two ways: First, we consider it in generating our instrument by capturing the potential for improvement in anemia prevalence. Second, we incorporate the state-level AMB ranking from its annual scorecard. This scorecard presents the performance metrics for IFA supplementation coverage across Indian states and UTs, based on the information from the Health Management Information System and AMB dashboard. From this, an AMB index is calculated as the average IFA supplementation coverage across selected beneficiary groups, with states and UTs ranked based on their performance. In our study, we use the AMB index 2018-19 to explore the heterogeneity in our results (see Supplementary Information for details).

3. Empirical specification

We hypothesize that anemia decreases the probability of school enrollment. An empirical concern, however, is that the improvements in hemoglobin concentration and reduction in anemia over time could be correlated with several unobserved factors. This may include the developments in local infrastructure, socio-economic and demographic conditions, and implementation of interventions and policies over time, which may bias the estimates. To alleviate this problem, we use several approaches. Firstly, to account for time-invariant unobserved heterogeneity at each cluster, we use cluster fixed effects and time fixed effects. Secondly, in the model, we add various time-varying cluster-level controls, capturing socioeconomic development of clusters over time (Coffey et al., 2018; Vyas et al., 2016). Thirdly, we incorporate the interaction terms between the cluster-level initial conditions and the time dummies to account for the potential confounders. Lastly, we use the IV approach to our estimation strategy, which we will discuss in detail later in this section.

We begin by estimating the following equation.

$$Y_{icst} = \beta_0 + \beta_1 Anemia_{icst} + \beta_2 X1_{icst} + \beta_3 X2_{cst} + \beta_4 X3_{cs0} \times D_t + \delta_c + \delta_t + \mu_{icst} \quad (1)$$

where *i, c, s, and t* index the individual adolescent, the NFHS cluster, the state, and the survey year, respectively. The outcome of interest Y_{icst} represents the individual adolescent's school enrollment. It takes the value of 1 if an adolescent attended school or college during the survey year, and 0 otherwise. $\beta_1$is the parameter of interest which captures the impact of adolescent anemia on the likelihood of school enrollment. The vector $X1_{icst}$ captures the observed individual and household characteristics. $X2_{cst}$ in the model accounts for the possibility that the anemia prevalence in a cluster could be correlated with local infrastructure and socio-economic development (see Section 2.2). As previously discussed, we also

incorporate an interaction term $X3_{cs0} \times D_t$, where $X3_{cs0}$ denotes the cluster-level baseline characteristics, and D_t is the time dummy. δ_c and δ_t are the cluster fixed effects and survey year fixed effects, which accounts for temporal variation due to national trends, educational and nutrition-related policies, and other unobserved macroeconomic shocks. μ_{icst} denotes the error term and the standard errors are clustered at the NFHS cluster level, assuming that the error term is correlated within each cluster-by-year level.

The empirical challenge to estimate equation (1) still exists due to potential endogeneity issues owing to unobserved factors, including local socioeconomic conditions, food prices, health infrastructure, disease environment, cultural norms, parental attitudes towards education and health, and food preferences. Additionally, reverse causality may arise if school attendance influences nutritional intake by school-based IFA supplementation through various initiatives, e.g., AMB and Weekly Iron and Folic Acid Supplementation (WIFS) program, that could affect the anemia prevalence[7]. Several methods exist to solve the endogeneity issues, each with its own limitations, and the selection is mainly guided by the type of data available (Shiferaw et al., 2014).

To address potential endogeneity concerns, we employ two IVs in our identification strategy. The first is the interaction term between the time-invariant state-level possession or sale of the beef ban, the beef-consuming group, and a time dummy. This captures variation in anemia driven by beef bans, which disproportionally affect certain dietary communities. State-level beef ban laws reduce access to one of the most affordable sources of dietary iron and animal protein for groups that traditionally eat beef than those who do not. By interacting

[7] The uptake of IFA coverage programs, especially WIFS, remains low, however; given the effectiveness of IFA supplementation prior research suggested to increase its coverage (De Neve et al., 2024; Rai, 2022; Sudfeld et al., 2020).

the beef ban status with the beef-consuming groups and a time dummy, we capture changes in hemoglobin levels arising from persistent non-health policy environments, whose impact may vary over time due to changes in the enforcement intensity, awareness, market conditions, or substitution behaviors in dietary intake. The time dummy ensures that the interaction captures any variation between 2015 and 2021, rather than merely static cross-sectional differences.

The second IV is the interaction term between the cluster-level initial anemia rate in 2015 and a time dummy. This leverages cross-cluster variation in baseline anemia prevalence to capture the potential for improvement over time. The key underlying assumption is that, following the introduction of the AMB program, clusters with higher anemia rates in 2015 experienced greater improvements in hemoglobin levels. This kind of variation has been widely used in prior research. For instance, Joe et al. (2022) found that the states with lower IFA coverage initially in 2017-18 saw greater improvement in IFA coverage under the AMB program in 2019-20. Similarly, Bleakley (2007) utilized geographic variation in pre-treatment hookworm infection rates across U.S. Southern states to demonstrate that the hookworm eradication program yielded larger benefits in regions with higher initial infection rates compared to those with low rates.

Fig. 3 illustrates the relationship between baseline anemia prevalence in 2015 and subsequent changes in anemia prevalence from 2015 to 2021. Our IV is motivated by the observed negative association between these two measures during the period that coincides with the implementation of the AMB strategy. This pattern suggests that the clusters with initially high anemia rates had higher room for improvement and were more likely to benefit from this program, resulting in significant improvements in hemoglobin levels over time.

[Fig. 3]

It is important to note that our instrument is not the AMB program, and we are not estimating the causal effect of this program. While one might argue considering this program as an IV, AMB is a national initiative, and its placement could be influenced by the state-level capacity and other unobserved characteristics. These factors may also influence the educational outcomes, introducing potential endogeneity concerns. Thus, we exploit the opportunity for anemia reduction, potentially due to this program, instead of using this non-random initiative as an IV.

We assume that the initial year anemia prevalence is plausibly exogenous, as it lies beyond the control of individual households. However, one might argue that it may not be completely exogenous if some time-varying unobservable factors correlate with both adolescent schooling and health conditions. The clusters with lower anemia prevalence may have had better socioeconomic conditions from the outset, which may lead to systematically different trends. Additionally, baseline differences in socioeconomic status and infrastructure may influence the extent to which dietary restrictions, such as those imposed by beef ban laws, affect hemoglobin levels. To mitigate these concerns, we incorporate a rich set of time-varying cluster controls[8] and the interaction terms between the clusters' initial conditions, such as anemia prevalence in the year 2010, the share of households with access to piped water, and the proportion of households holding BPL cards (a proxy for socioeconomic status) in 2015, and the time dummies. These variables help account for heterogeneous baseline conditions across clusters and allow for different time trends. For example, clusters with worse initial health conditions might exhibit different rates of improvement in school

[8] If changes in other development-related indicators in such areas predict some school participation changes over time, it would not necessarily show an identification problem *per se*, rather it will suggest the importance of clearly distinguishing the effects of key exposure from the correlated factors (e.g., Coffey et al. 2018).

participation compared to clusters with better health conditions, especially those with lower anemia rates. Thus, by accounting for differences in cluster-level initial year conditions, we reduce the risk that our IV may capture differential trends driven by pre-existing conditions.

Using both instruments is important for two reasons. First, they capture distinct and plausibly exogenous sources of variation, one arising from non-health policy induced dietary limitations that we expect to increase anemia among certain groups, and the other from initial health conditions that are expected to reduce anemia prevalence over time under the health policy initiative. Second, using both instruments jointly reduces reliance on a single source of variation and mitigates the risk of bias in our estimations owing to unobserved factors correlated with one of these channels. Since the beef ban policy was motivated more politically, its exogeneity to health outcomes is plausibly higher than the AMB policy potential. However, our IV, which is the interaction term of the state-level beef ban policy, respondents' group indicators, and the time dummy, has a limited variation over space. Since this IV offers only a local average treatment effect (LATE), we prefer to combine this IV with the interaction term between the cluster-level initial anemia and the time dummy.

We run the following first-stage estimation:

$$Anemia_{icst} = \alpha_0 + \alpha_1 Possesion\ or\ sale\ ban_s \times beef\ consumer_{icst} \times D_t + \alpha_2 Anemia_{cs} \times D_t + \alpha_3 \mathrm{H1}_{icst} + \alpha_4 \mathrm{H2}_{cst} + \alpha_5 \mathrm{H3}_{cs0} \times D_t + \varphi_c + \varphi_t + \varepsilon_{icst} \quad (2)$$

Where the first IV—$Possesion\ or\ sale\ ban_s \times beef\ consumer_{icst} \times D_t$ is generated by interacting the state-level beef ban dummy with a beef–consuming group indicator and a time dummy. The beef consuming group dummy variable indicates the traditional beef-eating groups which, using the information on religion and caste, we code as "1" for beef consumers such as Muslims, SC Hindus (also identified as Dalits), and Christians, and 0 for all other

ethnic and religious groups that do no traditionally consume beef, such as non-SC Hindus[9], Sikhs, Jains, Jewish, Parsis, Buddhists (including Neo-Buddhists), individuals with no religion and other religion[10]. This IV measures the differential impact of possession or sale bans in states with those restrictions compared to states without them, for individuals in beef-eating groups, relative to the changes observed among similar groups in non-beef ban states and among non–beef–eating groups across all states. The second IV—$Anemia2015_{cs} \times D_t$, is generated by interacting the cluster-level anemia prevalence in 2015 with the time dummy, capturing the potential for improvement in anemia reduction. Given that we generate geographical panel data and incorporate cluster fixed effects in the model, our underlying identification relies on within-cluster changes in adolescents' anemia and school participation between 2015 and 2021.

4. Empirical results

Table 1 presents the estimates of the impact of adolescent anemia on the probability of school enrollment. Panel A of Table 1 reports Ordinary Least Squares (OLS) estimates, while panels B and C display the first and the second stage of the Two Stage Least Squares (2SLS) estimations, respectively. Panel A shows that anemia is negatively associated with school enrollment. In Columns (1)–(3), the point estimates remain stable and statistically significant with the gradual inclusion of additional controls to the basic specification of cluster and time

[9] Prior work found a significant variation in the meat consumption among Scheduled Tribes (ST) (Adivasis), ranging from meat consumption to be vegetarian due to their economic constraints (Ferry, 2020). Therefore, following Dasgupta et al. (2023), we classify ST and other backward classes (OBC) as non-beef consumers, since their dietary patterns most closely resemble those of upper caste Hindus than those of SC Hindus.

[10] The observations for Jewish, Parsi, no religion, and other religions are small. Our estimates remain robust even if we drop these minorities.

fixed effects. For instance, Column (1) shows that adolescent anemia is associated with a 1.9 percentage point lower probability of school enrollment, including cluster and time fixed effects. Column (2) indicates that the estimated coefficient slightly declines to -0.018 with the addition of various cluster-level controls. Column (3), with the inclusion of full controls, estimates a 1.7 percentage point reduction in the probability of school enrollment for anemic adolescents compared to their non-anemic peers.

Panel B presents the first-stage results, where the dependent variable is the individual anemia dummy and the excluded instruments include the interaction term between the possession or sale ban and the beef consumer group, the time dummy, and the interaction between cluster-level anemia prevalence in 2015 and the time dummy. Both instruments are strongly correlated with the main explanatory variable across all specifications. More specifically, Column (3) shows that exposure to the possession or sale of beef bans increases the likelihood of anemia by 2.7 percentage points among beef-consuming groups than those who do not. As we will discuss later, this effect is absent for the non-beef-consuming communities, supporting its use as a valid instrument (see Section 4.2). For the second instrument, we find that a cluster with one percentage point higher anemia prevalence in the initial year experienced a 0.901 percentage point larger reduction in anemia prevalence between 2015 and 2021. Kleibergen-Paap (KP) rk Wald *F*-statistic is more than 2,000, exceeding the conventional critical values, rejecting concerns about the weak instruments. While both instruments are individually strong and pass the weak identification tests, the Hansen J-test indicates potential overidentification ($p < 0.001$). To address this, we estimate the main model using both IVs individually and show that the results are consistent in terms of direction and significance, reinforcing the robustness of our main findings (Supplementary Table S1). Supplementary Table S2 reports the reduced form estimations. Both the weak

instruments test and the overidentification tests are associated with large values of F (or J) statistics, likely to be due to our large sample size (the exact test results are available on request). For the reasons stated already, we mainly report the results using both IVs.

Panel C presents the second stage of 2SLS estimations from equation (1), showing the impact of anemia on school enrollment. Column (1) shows that adolescent anemia leads to a reduction in school enrollment by 5.1 percentage points. Column (2) indicates that the point estimate remains robust when including interactions between the cluster-level baseline characteristics and the time dummies, and time-varying cluster-level controls. The stable point estimates suggest that changes in anemia prevalence are not correlated with trends in other characteristics that may change over time. In Column (3), we find that adolescents suffering from anemia decrease their likelihood of school enrollment by 4.2 percentage points, including a full set of controls. This translates to a 6.2 % reduction in the likelihood of school enrollment compared to the sample mean. Taken together, the OLS and 2SLS estimates provide robust evidence that adolescent anemia has a significant negative impact on school enrollment[11].

[Table 1]

4.1 Heterogeneity of Anemia

Within the empirical estimation, we examine the heterogeneous effects of anemia on the school enrollment across adolescents' gender, relationship to the household head, area of residence, and the state-level AMB index

[11] Our estimates are robust if we use the cow slaughter ban instead of the possession or sale ban to generate the beef ban instrument (Supplementary Table S3). Our results (available upon request) also remain consistent if we drop the sample of pregnant girls.

4.1.1 Gender-specific effects

While our main findings indicate a significant negative impact of anemia on school enrollment, this effect may not be uniform across genders. To motivate disaggregated analysis, Fig. 4 illustrates the distribution of hemoglobin levels separately for girls and boys, along with gender specific anemia thresholds. The high density of adolescents marginally above the cutoff points suggests that, although not classified as anemic, many are still susceptible to iron deficiency. Additionally, a substantial proportion of adolescents, particularly girls, fall below these thresholds, suggesting a higher anemia prevalence among girls compared to boys. These patterns may be attributed to a combination of biological differences and gender-based social preferences.

[Fig. 4]

Prior evidence suggests that the girls are more likely to face nutritional disadvantages, such as unequal intra-household food allocation, lesser access to healthcare, and lower investment in female health and education, while boys are believed to receive more social preferences (Augsburg & Rodríguez-Lesmes, 2018; Jayachandran & Kuziemko, 2011; Hazarika, 2000; Das Gupta, 1987). These factors may enhance both the prevalence and consequences of anemia among girls more than among boys.

To formally assess this heterogeneity, Table 2 reports IV estimates separately for the female and male adolescents. Columns (1)-(2) present the effect of anemia on school enrollment among girls, while Columns (3)-(4) show such effects for boys. In Column (2), using a full set of controls, we find that anemia reduces the likelihood of school enrollment among girls by 3.4 percentage points, compared to their non-anemic counterparts. Conversely, the coefficient for boys in Column (4) is -0.319, statistically insignificant and imprecisely estimated due to a large standard error. Several factors may explain the absence

of a significant effect for boys. For instance, in our sample, 22% of boys are anemic compared to 55% of girls. This lower prevalence and reduced variability in anemia status among boys may result in weaker statistical power and imprecise estimates. Moreover, boys exhibit a relatively higher average school attendance rate (74%) than girls (68%). Even when affected by health shocks like anemia, boys might be less likely to withdraw from school due to higher perceived returns to education and larger parental investments in sons, as documented in the Indian context (Azam & Kingdon, 2013). Anemic boys who continue schooling may benefit from school-based nutritional supplementation initiatives, as part of the AMB strategy, which can help in mitigating the physical and cognitive impacts of anemia[12].

To explore further whether girls may face disparity in intra-household food allocation, in Supplementary Table S4, we explore the associations between the adolescent's gender and the household's nutrition investment behavior. The estimates reflect how females are less likely than males to receive nutritional food. Such preferential investments may suggest that girls are more vulnerable to anemia. The social disadvantages and nutritional disparity faced by girls may influence the effect of health shocks on their educational outcomes. Overall, these findings support the hypothesis that anemia imposes a disproportionate burden on girls, both in terms of prevalence and its negative effect on educational outcomes. This aligns with the broader evidence of gender based educational and nutritional disadvantages in South Asia (Jayachandran & Kuziemko, 2011).

[Table 2]

[12] Given the considerable uncertainty and lower statistical power in male subsample, caution is warranted when interpreting the lack of significant and imprecise effect for male adolescents.

4.1.2 Relationship with the head of the household

Our main model explores the impact of anemia on school enrollment among sample adolescents. However, the effect of health shocks like anemia may vary depending on the adolescent's relationship to the household head. It is plausible that biological children (sons/daughters) of the household head are less vulnerable to the adverse effects of health shocks, such as anemia, potentially due to differences in intra-household resource allocation and caregiving, than those who are not the children of the household head.

To test this hypothesis, we stratify the sample based on the adolescent's relationship to the household head. The variable takes 1 if the adolescent is a son or daughter of the household head, and 0 otherwise[13]. Table 3 reports the effect of anemia on school enrollment for both subgroups. Columns (1)-(2) report results for biological children (sons/daughters), while Columns (3)-(4) present estimates for adolescents who are not the children of the household head, with increasing sets of controls across specifications. More specifically, Column (2) shows that an increase in anemia reduces the probability of school enrollment by 3.1 percentage points for the biological children (sons/daughters), including full controls. Contrarily, Column (4) indicates a substantially larger effect—a 12.7 percentage point reduction in the likelihood of school enrollment for adolescents who are not the children of the household head. These findings support our hypothesis that intra-household resource allocations are not uniform, particularly resource allocation and caregiving priorities may be skewed in favor of the children of the household head, and individuals who are not the offspring of the household head may face disadvantages in terms of intra-household resource

[13] The percentage of the sample with this dummy variable taking 1 is 78%. In the remaining 22% for which the dummy variable takes the value of 0, the largest majority is son/daughter-in-law of household head (4%), followed by the grandchild (10%).

allocation[14]. Supplementary Fig. S2 visualizes the heterogeneity in the impact of anemia on school enrollment by adolescents' relationships to the household head.

To explore further, in Supplementary Table S5, we conduct a supplementary sub-sample analysis by household structure (nuclear vs. non-nuclear). The findings indicate that the negative effect of anemia on school enrollment is more pronounced in non-nuclear households than in nuclear households. This finding supports the hypothesis that caregiving and resource distribution may be more unequal in the extended family arrangements.

[Table 3]

4.1.3 Area of residence

Heterogeneity in the relationship between anemia and school enrollment may arise depending on the area of residence. This is because the rural-urban disparities often reflect variations in access to healthcare, education, and awareness, largely driven by economic and infrastructural constraints. We therefore hypothesize that anemia has a larger effect on hemoglobin levels in rural areas than in urban areas.

Table 4 examines whether the effect of anemia on school enrollment differs between urban and rural settings. Columns (1) − (2) show that in rural areas, anemia significantly reduces school enrollment. For instance, Column (2) indicates that adolescents' anemia significantly lowers the probability of being enrolled in school by 4.1 percentage points.

[14] Household fixed effects implicitly assume uniform treatment of individuals within a household, which may obscure intra-household heterogeneity, particularly in the extended family settings where caregiving and resource allocation are often uneven. Household fixed effects may bias sub-sample estimates, especially if the sample is non-randomly distributed across extended and nuclear households. Consequently, employing household fixed effects in our context may bias the results by misrepresenting variation across different family structures.

Conversely, Columns (3)− (4) show that although the estimated coefficients are negative in urban areas, they are statistically insignificant. These findings suggest that the adverse educational consequences of anemia are concentrated in rural settings more than in urban areas.

One plausible explanation for this heterogeneity is that rural adolescents may be more vulnerable to the consequences of anemia due to limited healthcare access, lower household awareness, and weaker institutional support. Conversely, urban adolescents may benefit from better healthcare access, higher awareness, and a more supportive school environment. These factors can mitigate the adverse effects of anemia on school attendance.

[Table 4]

4.1.4 AMB index score intensity

As discussed earlier, the AMB program was rolled out nationwide beginning in 2017–18 and provides an AMB index reflecting state-level IFA supplementation coverage (MoFHW, 2018). It is plausible that heterogeneity in the effect of anemia on school enrollment may arise from the variation in the intensity of IFA implementation across states. In states where IFA coverage remained low, the reduction in anemia may be limited. Therefore, we hypothesize that the adverse effect of anemia on attending school should be more pronounced in states with lower IFA supplementation coverage than in those with relatively higher coverage.

Table 5 tests this hypothesis by stratifying states into low, medium, and high AMB index groups using thresholds defined by the AMB program. Specifically, states with an AMB index score below 25 in 2018-19 are classified as low coverage, those with scores 25 to 50 as medium, and those above 50 as high coverage. Column (1) shows that in low IFA

coverage states, anemia significantly reduces the likelihood of school enrollment by 5.1 percentage points. Column (2) indicates a similar but slightly smaller effect of 4.8 percentage points in states with medium AMB index scores. Conversely, Column (3) shows no significant effect in high IFA coverage states, as indicated by a coefficient of 0.008. These findings suggest that the effectiveness of the AMB program in mitigating the adverse impacts of anemia varies with the intensity of IFA implementation.

To ensure robustness to threshold choice, Supplementary Table S6 reclassifies the AMB index into quintiles. The findings remain consistent mainly in the sense that the adolescents in states with lower IFA coverage experience adverse effects. Further, in Supplementary Table S7, using a binary split at the median AMB index score of 28.35, our findings show consistency that the effect of anemia differs with the intensity of program implementation.

[Table 5]

4.2 Falsification tests

In employing the beef ban as an IV, our key assumption is that the beef ban disproportionally affects groups that traditionally consume beef, as their dietary patterns would be directly influenced. Conversely, we do not expect the ban to affect communities that do not traditionally consume beef. To test this assumption, we conduct a falsification test presented in Table 6, where we estimate the relationship between the beef ban and anemia dummy separately for the non-beef-consumers and the beef-consumers. Columns (1) − (2) estimate equation (3) for non-beef-consuming groups, serving as a placebo group. Columns (3) − (4) estimate equation (2) for the beef consumer groups.

$$Anemia_{icst} = \gamma_0 + \gamma_1(Possesion\ or\ sale\ ban_s \times NonBeef\ consumer_{icst} \times D_t) + \gamma_2 \mathrm{H1}_{icst} + \gamma_3 \mathrm{H2}_{cst} + \gamma_4 \mathrm{H3}_{cs0} \times D_t + \lambda_c + \lambda_t + \upsilon_{icst} \quad (3)$$

where the exposure variable is the interaction term between possession or sale ban and non-beef consumers, and the time dummy. $\mathrm{H1}_{icst}$ and $\mathrm{H2}_{cst}$ are the vectors for individual, household, and cluster-level controls, respectively, and $\mathrm{H3}_{cs0} \times D_t$ are the interactions between the cluster's initial conditions and time dummies. λ_c and λ_t are the cluster and the time fixed effects, respectively.

In Columns (1) − (2) of Table 6, the point estimates are small and statistically insignificant, with an effect size of -0.002 and -0.004, respectively, indicating that the beef ban had no measurable impact on non-beef consumers (Dasgupta et al., 2023). Conversely, Columns (3) − (4) show that the beef ban instrument is significantly correlated with anemia dummy among beef consumers, with an effect size of 0.079 and 0.071, respectively, providing support to the validity of our identification strategy. Additionally, Columns (2) and (4) also incorporate the second instrument—cluster-level initial anemia prevalence times time dummy in equations (2) and (3), which captures the potential for improvement in anemia for everyone over time within a cluster. The consistent results further support the validity of our approach.

[Table 6]

As explained earlier, we include the interaction terms cluster-level initial values times time dummies to mitigate concerns that clusters with initially lower anemia may also have had better socioeconomic conditions from the outset. To further assess the possibility that areas with significant improvements in hemoglobin levels may also have experienced differential socioeconomic development that could independently influence school

participation, we conduct falsification tests using the instrument— Initial year cluster's anemia prevalence times time dummy. Specifically, we examine whether the instrument correlates with local socioeconomic indicators that could plausibly influence school attendance. This helps to verify that our IV is not capturing underlying trends in local economic development, and the findings are not driven by other characteristics that might have also changed over time as a part of local economic growth. We consider socioeconomic indicators as dependent variables, including the share of households holding a BPL card, land ownership usually used for agriculture, access to the internet, and piped water facilities, serving as proxies for local socioeconomic conditions and living standards. We expect the coefficients of these indicators to be insignificant and not systematically predict improvements in these outcomes.

Table 7 reports the reduced-form estimates. Across all indicators, the coefficients on the instruments are small in magnitude and statistically insignificant. These findings support the validity of our instrument, indicating that it is not correlated with concurrent improvements in local socioeconomic conditions. Importantly, these findings complement the main results in Table 1, where the estimated effect of anemia on school attendance remains stable even after including time-varying economic controls. Therefore, the significant effect of anemia on school attendance is more likely attributable to change in anemia prevalence rather than concurrent socioeconomic developments.

[Table 7]

We further assess whether improvements in anemia in a cluster might reflect broader changes in general health outcomes, which are unrelated to hemoglobin levels and should not plausibly respond to either instrument. Specifically, we use two health outcomes available in NFHS, including thyroid disorders and sexually transmitted infections (STIs), which are not

biologically linked to iron intake, hemoglobin levels, or beef consumption. If observed changes in school attendance were instead driven by general improvements in healthcare access, economic conditions, or local development, we would expect corresponding improvements in these unrelated health outcomes.

Table 8 estimates our main IV specification using thyroid disorders and STIs dummies as alternative dependent variables. In Columns (1) and (2), across both outcomes, the coefficients are close to zero and insignificant, with an effect size of 0.0035 and 0.0003, respectively. These results indicate that neither instrument predicts changes in unrelated health conditions, supporting the assumption that the estimated effect of anemia on school participation is not driven by broader changes in general health conditions. Overall, these falsification tests support the validity of our instruments.

[Table 8]

4.3 Robustness checks

In this section, we perform a range of robustness checks to test the validity and stability of estimates. Firstly, our main exposure variable is a binary indicator of anemia. As a robustness check, we redefine the exposure using hemoglobin levels (g/dL) as a continuous indicator to assess whether our results are sensitive to the operational definition of anemia. Consistent results across both specifications would strengthen the validity of our main findings. In Appendix Table A2, we estimate equation (1) using hemoglobin levels as the key independent variable and find that higher hemoglobin levels significantly increase the likelihood of school enrollment. These findings indicate that our estimates from Table 1 remain robust to the alternative definition, suggesting that anemia negatively influences school participation. Moreover, the effect of anemia on school enrollment may differ by severity. To explore this possibility, we perform a dose-response analysis by disaggregating

anemia into any anemia, moderate anemia, and severe anemia. The results shown in Supplementary Table S8 suggest that the anemia severity matters[15].

Secondly, in the main analysis, we construct a geographic panel dataset by matching clusters from the 2015 and 2021 waves located within a 10 km distance, treating them as analogous units. However, such geographic matching may introduce measurement error and obscure potential differences in demographic and socioeconomic conditions between clusters. To assess the robustness of findings and to address that our findings may be sensitive to the selection of the distance threshold, Appendix Table A3 presents alternative specifications to the main model employing varying thresholds of 3 km, 5 km, 7 km, and 9 km to generate the geographic panel. Overall, the results are consistent across specifications, although the magnitude of the estimated effect tends to decrease slightly as the matching distance threshold increases.[16]

Thirdly, as we explained earlier, our main model includes interaction terms between cluster-level initial values and the post-period time dummies. These terms help mitigate concerns that clusters with initially lower anemia may have also had better socioeconomic

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[15] We observe that moderate anemia meaningfully reduces school enrollment; however, the point estimates of severe anemia are substantially larger. This may plausibly reflect both, the serious health effects of severe anemia and the small sample of severely anemic adolescents (1.92% in our sample), which might result in inflated and less stable estimates. Therefore, while the direction of the effect is consistent with the main results, caution is warranted while interpreting the magnitude of severe anemia.

[16] We treat the geographic clusters as analogous units; however, time-varying characteristics naturally evolve due to demographic and socioeconomic changes. Therefore, to validate the matching we focus on possible time-invariant characteristics that should remain stable if the matched clusters are similar. Specifically, we compare the cluster's ethnic composition. altitude, and the distance of a cluster's central point to the district centroid. Supplementary Table S9 reports mean comparison tests between these characteristics across both NFHS waves, and the *t*-test statistics suggest no significant differences across matched clusters.

conditions from the beginning. By including these interactions, we aim to ensure that our results are not sensitive to these inclusions and the estimates reflect the impact of changes in anemia on school participation and are not confounded by unobserved heterogeneity. Baseline cluster-level characteristics may vary, and the effect of anemia prevalence may differ across clusters depending on their initial conditions.

One of the interaction terms is cluster-level anemia prevalence times time dummy. In Section 2.1, we elucidate that we use a 10 km radius to generate cluster-level anemia prevalence in the year 2010. Given that NFHS-3 (2005-06) lacks georeferenced cluster identifiers, we use spatial information from IHME to extract anemia information in 2010. Specifically, we calculate the average anemia prevalence within a 10-km radius around each cluster's GPS point. Using this approach is meaningful because we observed that the direct anemia data from IHME were unavailable for a significant number of clusters. By using a 10-km radius strategy, we can retain a sample of 17,946 geographic clusters; however, this approach may involve some degree of measurement error. To test the sensitivity of our results to this measurement approach, Appendix Table A4 reports alternative specifications. In Columns (1) and (2), we re-estimate the model using a 5-km radius and exactly at each cluster without using any buffer around the cluster, respectively, which leads to some sample loss but ensures better precision. The results show consistency using both alternative estimations. Overall, this method allows us to add the pre-existing cluster-level anemia prevalence information in our estimations while retaining the sample clusters. Column (3) shows that our findings remain consistent when we exclude the interactions between cluster-level initial values and the time dummies, suggesting the robustness of the results. In Column (4), as a robustness check, we replace the time fixed effects with state-by-time fixed effects to account for any state-specific shocks or policy interventions that may vary over time. The results

show consistency and suggest that our findings may not be driven by state-level time-varying factors.

Fourthly, to assess whether the beef-ban instrument might operate through income shocks in food-related sectors rather than through anemia, we draw on both external evidence and our data. We first rely on Dasgupta et al. (2023), who analyze earlier National Sample Survey waves (1983–2012), a period before our study, where detailed meat consumption is directly observed, whereas NFHS does not collect the detailed information on the types of meat that the individuals consume. The authors show that longstanding state-level beef bans do not necessarily reduce beef consumption, because banned items are difficult to measure, but they find a significant decline in mutton consumption among minorities. They interpret this as reflecting fear of vigilant violence and misidentification of red meat, which discourages consumption of visible red-meat substitutes. Importantly, they found a negative association with red meat consumption, and even a significant and positive association with "any meat" consumption, suggesting some evidence of substitution toward white meat rather than a broad reduction in food intake.

Our findings mirror this long-run substitution mechanism. In Supplementary Table S10, using NFHS data, which capture consumption frequency but do not distinguish between red meat and chicken, we find that the instrument is significantly and positively associated with any meat (chicken or meat) consumption, fish, eggs, and vegetable consumption, while showing mixed or null effects for other foods. This pattern may suggest that beef-eating groups in long-standing beef-ban states may compensate for reduced access to red meat by shifting toward other protein sources. Therefore, a positive and significant coefficient on "any meat consumption" is consistent with the mechanism documented by Dasgupta et al. (2023). Taken together, this evidence suggests that beef bans primarily operate by altering the

composition of diets among beef-eating groups, rather than through income shocks in meat-related sectors[17].

Fifth, we re-estimate the model by adding the chicken or meat consumption frequency. However, we do not include this measure in the main specification due to the potential endogeneity of meat consumption. Supplementary Table S11 shows that frequent consumption of meat significantly reduces the likelihood of anemia compared to those who never consume meat. Moreover, we find that our main results on the effect of anemia on school enrollment remain robust with and without controlling for meat consumption frequency. In Column (2), the coefficient for meat consumption is negative and statistically significant. A plausible explanation for this effect might be related to social and cultural factors in India, where traditionally vegetarian groups, such as some upper caste Hindus, Jains, and Sikhs, tend to place a higher value on education and achieve higher school enrollment. Conversely, frequently meat-consuming groups, often belonging to religious minorities and socially disadvantaged castes, might face structural barriers to schooling. Lastly, Supplementary Table S12 reports an additional robustness check, where we find that having a blood transfusion history to address health-related concerns is significantly correlated with adolescent anemia. Furthermore, we show that the IV estimates remain robust with and without controlling for ever-received blood transfusion indicator, suggesting that blood transfusion history has no independent effect on current school attendance, and the anemia and schooling relationship is not confounded by this subgroup.

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[17] We further explore adolescent labor as a proxy for contemporaneous income shocks. Using the NFHS "currently working" indicator, we find no significant correlation between the beef-ban IV and adolescent labor (results available upon request). Together with the absence of systematic decline in food consumption, this may suggest that the beef-ban instrument is unlikely to capture large income shocks in food-related sectors.

5. Conclusion

This study provides large-scale empirical evidence that improving adolescents' health, particularly anemia, can have significant benefits for educational outcomes in India, a country with both one of the world's highest anemia burdens and the largest out-of-school adolescent population. Our results provide evidence of the effectiveness of anemia reduction in improving adolescents' school enrollment. The findings underscore that adolescent anemia is not only a public health issue but also a binding constraint on human capital development. We find that anemia among adolescents reduces the likelihood of school enrollment by 3.9 percentage points. This effect is substantial, given that about 52 million adolescents of secondary school age were out of school in the country (UNESCO, 2024). Our findings indicate that adolescent anemia is a significant barrier to school enrollment, particularly for girls, those living in rural areas, non-biological children of the household head, and those in states with a lower AMB index, depending on the IFA coverage, than their counterparts.

The study results suggest that the improvement in school enrollment would have been better if adolescent anemia in general had been reduced in India. The school retention strategies should integrate targeted anemia reduction initiatives, with a particular focus on vulnerable subpopulations and areas with low IFA supplementation coverage, as highlighted in this study. Broader strategies that target adolescents, ensuring the effective implementation of initiatives including AMB and WIFS programs, could improve both the adolescents' health and educational outcomes. By linking remediable health conditions to school participation, this study highlights an actionable pathway to accelerate progress concerning SDG-2 on improved nutrition and SDG-4 on universal secondary education.

References

Anand, T., Rahi, M., Sharma, P., & Ingle, G. K. (2014). Issues in prevention of iron deficiency anemia in India. Nutrition, 30(7), 764–770. https://doi.org/10.1016/j.nut.2013.11.022

Augsburg, B., & Rodríguez-Lesmes, P. A. (2018). Sanitation and child health in India. *World Development*, *107*, 22–39. https://doi.org/10.1016/j.worlddev.2018.02.005

Azam, M., & Kingdon, G. G. (2013). Are Girls the Fairer Sex in India? Revisiting Intra-Household Allocation of Education Expenditure. *World Development*, *42*, 143–164. https://doi.org/10.1016/j.worlddev.2012.09.003

Behrman, J. R. (1996). THE IMPACT OF HEALTH AND NUTRITION ON EDUCATION. The World Bank Research Observer, 11(1), 23–37. https://doi.org/10.1093/wbro/11.1.23

Bleakley, H. (2007). Disease and Development: Evidence from Hookworm Eradication in the American South. The Quarterly Journal of Economics, 122(1), 73–117. https://doi.org/10.1162/qjec.121.1.73

Bobonis, G. J., Miguel, E., & Puri-Sharma, C. (2006). Anemia and School Participation. The Journal of Human Resources, 41(4), 692–721. https://www.jstor.org/stable/40057287

Chakrabarty, M., Singh, A., Singh, S., & Chowdhury, S. (2023). Is the burden of anaemia among Indian adolescent women increasing? Evidence from Indian Demographic and Health Surveys (2015-21). *PLOS Global Public Health*, *3*(9), e0002117. https://doi.org/10.1371/journal.pgph.0002117

Chaparro, C. M., & Suchdev, P. S. (2019). Anemia epidemiology, pathophysiology, and etiology in low- and middle-income countries. Annals of the New York Academy of Sciences, 1450(1), 15–31. https://doi.org/10.1111/nyas.14092

Children and adolescents out-of school. (n.d.). Our World in Data. Retrieved August 15, 2025, from https://ourworldindata.org/grapher/children-and-youth-out-of-school?time=2004..latest

Chong, A., Cohen, I., Field, E., Nakasone, E., & Torero, M. (2016). Iron Deficiency and Schooling Attainment in Peru. American Economic Journal: Applied Economics, 8(4), 222–255. https://doi.org/10.1257/app.20140494

Coffey, D., Geruso, M., & Spears, D. (2018). Sanitation, Disease Externalities and Anaemia: Evidence From Nepal. The Economic Journal, 128(611), 1395–1432. https://doi.org/10.1111/ecoj.12491

Currie, J. (2009). Healthy, Wealthy, and Wise: Socioeconomic Status, Poor Health in Childhood, and Human Capital Development. Journal of Economic Literature, 47(1), 87–122. https://doi.org/10.1257/jel.47.1.87

Dasgupta, A., Majid, F., & Orman, W. H. (2023). The nutritional cost of beef bans in India. Journal of Development Economics, 163, 103104. https://doi.org/10.1016/j.jdeveco.2023.103104

Dasgupta, P., & Ray, D. (1986). Inequality as a Determinant of Malnutrition and Unemployment: Theory. The Economic Journal, 96, 1011-34.

Gupta, M. D. (1987). Selective discrimination against female children in rural Punjab, India. *Population and development review*, 77-100.

De Neve, J.-W., Karlsson, O., Rai, R. K., Kumar, S., & Vollmer, S. (2024). Relationship between adolescent anemia and school attendance observed during a nationally representative survey in India. Communications Medicine, 4(1), 1–9. https://doi.org/10.1038/s43856-024-00533-8

Ezzati, M., Lopez, A. D., Rodgers, A. A., & Murray, C. J. L. (2004). Comparative quantification of health risks: Global and regional burden of disease attributable to selected major risk factors. World Health Organization. https://iris.who.int/handle/10665/42770

Ferry, M. (2020). What's India's Beef with Meat? Hindu Orthopraxis and Food Transition in India Since the 1980s. Sociological Forum, 35(2), 511–534. https://doi.org/10.1111/socf.12592

Grantham-McGregor, S., & Ani, C. (2001). A Review of Studies on the Effect of Iron Deficiency on Cognitive Development in Children. The Journal of Nutrition, 131(2), 649S-668S. https://doi.org/10.1093/jn/131.2.649S

Hazarika, G. (2000). Gender differences in children's nutrition and access to health care in Pakistan. *The Journal of Development Studies*, *37*(1), 73–92. http://dx.doi.org/10.1080/713600059

Hanif, A., Nakano, Y., & Matsushima, M. (2024, May). *Effect of community-level sanitation on women's hemoglobin levels: Evidence from Sub-Saharan Africa.* Paper presented at the 57th Annual Meeting of the Canadian Economic Association.

Harris, I., Osborn, T. J., Jones, P., & Lister, D. (2020). Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset. Scientific Data, 7(1), 109. https://doi.org/10.1038/s41597-020-0453-3

Haas, J. D., & Brownlie, T. (2001). Iron deficiency and reduced work capacity: A critical review of the research to determine a causal relationship. The Journal of Nutrition, 131(2S-2), 676S-688S; discussion 688S-690S. https://doi.org/10.1093/jn/131.2.676S

Halterman, J. S., Kaczorowski, J. M., Aligne, C. A., Auinger, P., & Szilagyi, P. G. (2001). Iron deficiency and cognitive achievement among school-aged children and adolescents in the United States. *Pediatrics*, *107*(6), 1381–1386. https://doi.org/10.1542/peds.107.6.1381

Institute for Health Metrics and Evaluation (IHME). HIV Incidence & Mortality. Seattle, WA: IHME, University of Washington, 2021. Available from https://vizhub.healthdata.org/lbd/hiv-inc-mort(Accessed [15-05-2025])

International Institute for Population Sciences (IIPS) and ICF (2017). National Family Health Survey (NFHS-4), 2015-16: India (IIPS, 2017).

International Institute for Population Sciences (IIPS) and ICF (2021). National Family Health Survey (NFHS-5), 2019-21: India (IIPS, 2021).

Joe, W., Rinju, Patel, N., Alambusha, R., Kulkarni, B., Yadav, K., & Sethi, V. (2022). Coverage of iron and folic acid supplementation in India: Progress under the Anemia Mukt Bharat strategy 2017-20. Health Policy and Planning, 37(5), 597–606. https://doi.org/10.1093/heapol/czac015

Jayachandran, S., & Kuziemko, I. (2011). Why do mothers breastfeed girls less than boys? Evidence and implications for child health in India. *The Quarterly Journal of Economics*, *126*(3), 1485–1538. https://doi.org/10.1093/qje/qjr029

Kinyoki, D., Osgood-Zimmerman, A. E., Bhattacharjee, N. V., Local Burden of Disease Anaemia Collaborators, Kassebaum, N. J., & Hay, S. I. (2021). Anemia prevalence in women of reproductive age in low- and middle-income countries between 2000 and 2018. Nature Medicine, 27(10), 1761–1782. https://doi.org/10.1038/s41591-021-01498-0

Krämer, M., Kumar, S., & Vollmer, S. (2021a). Anemia, diet, and cognitive development: Impact of health information on diet quality and child nutrition in rural India. Journal of Economic Behavior & Organization, 190, 495–523. https://doi.org/10.1016/j.jebo.2021.06.043

Krämer, M., Kumar, S., & Vollmer, S. (2021b). Improving Child Health and Cognition: Evidence from a School-Based Nutrition Intervention in India. Review of Economics and Statistics, 103(5), 818–834. https://doi.org/10.1162/rest_a_00950

Ministry of Health and Family Welfare (MoHFW) (2018). *Anemia Mukt Bharat Dashboard*. Accessed July 26, 2025, https://anemiamuktbharat.info/resources/home#AMB%20Score%20Cards.

Miguel, E., & Kremer, M. (2004). Worms: Identifying Impacts on Education and Health in the Presence of Treatment Externalities. Econometrica, 72(1), 159–217. https://doi.org/10.1111/j.1468-0262.2004.00481.x

More, S., Shivkumar, V. B., Gangane, N., & Shende, S. (2013). Effects of iron deficiency on cognitive function in school going adolescent females in rural area of central India. Anemia, 2013, 819136. https://doi.org/10.1155/2013/819136

Nguyen, P. H., Walia, M., Pant, A., Menon, P., & Scott, S. (2022). Changes in anemia and anthropometry during adolescence predict learning outcomes: Findings from a 3-year longitudinal study in India. The American Journal of Clinical Nutrition, 115(6), 1549–1558. https://doi.org/10.1093/ajcn/nqac028

Rai, R. K. (2022). Iron-and-folic-acid supplementation among adolescents (aged 10-19 years) in two North Indian States, 2015-2016: A sex-stratified analysis. *Public Health Nutrition*, *25*(3), 617–622. https://doi.org/10.1017/S136898002000508X

Sudfeld, C. R., Rai, R. K., Barik, A., Valadez, J. J., & Fawzi, W. W. (2020). Population-level effective coverage of adolescent weekly iron and folic acid supplementation is low in rural West Bengal, India. *Public Health Nutrition*, *23*(15), 2819–2823. https://doi.org/10.1017/S1368980020000932

Shiferaw, B., Kassie, M., Jaleta, M., & Yirga, C. (2014). Adoption of improved wheat varieties and impacts on household food security in Ethiopia. Food Policy, 44, 272–284. https://doi.org/10.1016/j.foodpol.2013.09.012

Stevens, G. A., Finucane, M. M., De-Regil, L. M., Paciorek, C. J., Flaxman, S. R., Branca, F., Peña-Rosas, J. P., Bhutta, Z. A., & Ezzati, M. (2013). Global, regional, and

national trends in haemoglobin concentration and prevalence of total and severe anaemia in children and pregnant and non-pregnant women for 1995–2011: A systematic analysis of population-representative data. The Lancet Global Health, 1(1), e16–e25. https://doi.org/10.1016/S2214-109X(13)70001-9

Vyas, S., Kov, P., Smets, S., & Spears, D. (2016). Disease externalities and net nutrition: Evidence from changes in sanitation and child height in Cambodia, 2005–2010. Economics and Human Biology, 23, 235–245. https://doi.org/10.1016/j.ehb.2016.10.002

UNESCO (2024). UNESCO Institute for Statistics (UIS). Retrieved August 13, 2024, from https://databrowser.uis.unesco.org/browser/?type=indicator&search=ou-of-school

UNESCO (2025). UNESCO Institute for Statistics, & Global Education Monitoring Report Team. *SDG4 scorecard progress report on national benchmarks: focus on the out-of-school rate*. Retrieved August 13, 2024, from https://unesdoc.unesco.org/ark:/48223/pf0000393833

WHO (2024). Guideline on haemoglobin cutoffs to define anaemia in individuals and populations. Retrieved May 2025, from https://iris.who.int/

WHO (2023). Women's Health. Retrieved March 2024, from https://www.who.int/news/item/12-05-2023-who-calls-for-accelerated-action-to-reduce-anaemia

Table 1. Effect of adolescent anemia on school enrollment

	School enrollment		
VARIABLES	(1)	(2)	(3)
Panel A: OLS			
Anemia (1=yes)	-0.019***	-0.018***	-0.017***
	(0.002)	(0.002)	(0.002)
	Anemia		
Panel B: First Stage			
Possession or sale ban × beef-consumer × time dummy	0.019***	0.029***	0.027***
	(0.005)	(0.005)	(0.005)
Cluster-level anemia prevalence 2015 × time dummy	-1.013***	-1.014***	-0.902***
	(0.013)	(0.013)	(0.013)
	School enrollment		
Panel C: Second Stage			
Anemia (1=yes)	-0.052***	-0.053***	-0.042***
	(0.014)	(0.013)	(0.014)
Cluster FE	✓	✓	✓
Time FE	✓	✓	✓
Cluster initial characteristics × time dummy		✓	✓
Time-varying cluster controls		✓	✓
Household and Individual controls			✓
Mean of the dependent variable	0.688	0.688	0.688
Observations	149,365	149,365	149,365

Notes: In panels A and C, the key outcome variable is a binary indicator for adolescent anemia. In panel B, the excluded instruments are the possession or sale ban × beef-consumer × time dummy, and the cluster-level anemia prevalence 2015 × time dummy. All specifications include cluster and time fixed effects (FE). Column (2) incorporates interactions between cluster-level initial values and time dummies, along with cluster-level controls such as the proportions of households with access to piped water, BPL cards, and internet access. Cluster-level average temperature and precipitation are also controlled. Standard errors clustered at the NFHS cluster-by-year level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2. Effect of adolescent anemia on school enrollment by gender (IV)

	School enrollment			
	Girls		Boys	
VARIABLES	(1)	(2)	(3)	(4)
Anemia (1=yes)	-0.034**	-0.034**	-0.45*	-0.319
	(0.016)	(0.015)	(0.246)	(0.220)
Cluster FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Cluster initial characteristics × time dummy		✓		✓
Controls		✓		✓
Mean of the dependent variable	0.681	0.681	0.739	0.739
Observations	130,303	130,303	16,019	16,019

Notes: Standard errors clustered at the NFHS cluster-by-year level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3. Effect of anemia on school enrollment by relationship with the household head (IV)

	School enrollment			
	Biological child (son/daughter)		Not a biological child	
VARIABLES	(1)	(2)	(3)	(4)
Anemia (1=yes)	-0.029*	-0.031*	-0.130***	-0.127***
	(0.015)	(0.016)	(0.048)	(0.044)
Cluster FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Cluster initial characteristics × time dummy		✓		✓
Controls		✓		✓
Observations	116, 137	116,137	27,862	27,862

Notes: Standard errors clustered at the NFHS cluster-by-year level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Effect of anemia on school enrollment by the area of residence (IV)

	School enrollment			
	Rural		Urban	
VARIABLES	(1)	(2)	(3)	(4)
Anemia (1=yes)	-0.051***	-0.041***	-0.040	-0.038
	(0.017)	(0.017)	(0.031)	(0.033)
Cluster FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Cluster initial characteristics × time dummy		✓		✓
Controls		✓		✓
Observations	111,600	111,600	36,981	36,981

Notes: Standard errors clustered at the NFHS cluster-by-year level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Effect of anemia on current school attendance by AMB index (State level IFA coverage) (IV)

	School enrollment		
	(1)	(2)	(3)
VARIABLES	AMB index low	AMB index medium	AMB index high
Anemia (1=yes)	-0.051*	-0.048**	0.008
	(0.026)	(0.020)	(0.038)
Cluster FE	✓	✓	✓
Time FE	✓	✓	✓
Controls	✓	✓	✓
Observations	49,109	76,449	23,807

Notes: Standard errors clustered at the NFHS cluster-by-year level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Falsification tests: Relationship between anemia and IV (sale or possession of beef ban)

	Anemia			
	(1)	(2)	(3)	(4)
VARIABLES	Non-beef consuming group		Beef consuming group	
Possession or sale ban × non-beef-consumer × time dummy	-0.002	-0.004		
	(0.0084)	(0.0080)		
Possession or sale ban × beef-consumer × time dummy			0.079***	0.0715***
			(0.0125)	(0.0117)
Cluster-level anemia prevalence 2015 × time dummy		-0.890***		-0.887***
		(0.0186)		(0.0274)
Cluster FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	87,635	87,635	57,541	57,541

Standard errors clustered at the NFHS cluster-by-year level are reported in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 7. Falsification tests. Relationship between socioeconomic indicators and IV (Cluster-level anemia 2015 × time dummy)

	BPL card	Land	Internet	Piped water
VARIABLES	(1)	(2)	(3)	(4)
Cluster-level anemia 2015 × time dummy	-0.0017	0.0042	0.0086	3.63e-05
	(0.0084)	(0.0097)	(0.0084)	(0.0092)
Cluster FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	149,113	149,365	149,365	149,365

Notes: The indicators related to socioeconomic status are reflected in column headers, which comprise the proportions of households having a BPL card, piped water sources, internet, and land mainly usable for agriculture in a cluster. Standard errors clustered at the NFHS cluster-by-year level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Falsification tests. Relationship of instruments with the alternative outcome

VARIABLES	Thyroid disorder	STIs
	(1)	(2)
Anemia (1=yes)	0.0035	-0.0003
	(0.0023)	(0.0007)
Cluster FE	✓	✓
Time FE	✓	✓
Controls	✓	✓
Observations	147,566	148,376

Notes: The alternative placebo outcomes are thyroid disorder and sexually transmitted infections (STIs) dummy. The dependent variables are the indicators unrelated to anemia and hemoglobin levels. Standard errors clustered at the NFHS cluster-by-year level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix A

Table A1. Summary Statistics

Years	2015 round		2021 round	
Variables	Mean	SD.	Mean	SD.
Anemia (1=yes)	0.476	0.499	0.554	0.497
Hemoglobin level (g/dL)	12.006	1.751	11.798	1.708
School enrollment (1=yes)	0.678	0.467	0.701	0.458
Adolescent age (years)	16.528	1.136	16.525	1.131
Adolescent gender (1=male)	0.134	0.341	0.119	0.323
Adolescent BMI	19.390	2.893	19.629	3.080
Household head gender (1=male)	0.862	0.345	0.837	0.369
Household head educated	0.908	0.288	0.747	0.434
Household structure (1=nuclear)	0.541	0.498	0.563	0.496
Urban dummy	0.261	0.439	0.238	0.426
Religion of household head (1=Hindu,…,8= other)	1.497	1.213	1.493	1.234
Household has access to piped water	0.383	0.486	0.431	0.495
Household has access to the internet	0.119	0.323	0.542	0.498
Share of access to piped water in a cluster	0.384	0.383	0.434	0.368
Share of access to the BPL card in a cluster	0.389	0.261	0.471	0.272
Share of access to the internet in a cluster	0.106	0.155	0.497	0.241
Temperature (Celsius)	24.514	4.019	24.447	3.822
Precipitation (mm)	105.658	54.158	111.785	64.080
Beef-consuming community dummy	0.403	0.491	0.408	0.491
Possession or sale ban dummy	0.615	0.487	0.613	0.487
Number of clusters	17,933		17,933	
Observations	78,737		70,628	

Notes: Table reports summary statistics for two rounds NFHS-4 (2015-16) and NFHS-5 (2019-2021). The observations are the adolescents aged 15-18.

Table A2. Effect of hemoglobin levels on school enrollment

	School enrollment	Hemoglobin	School enrollment
	(1)	(2)	(3)
VARIABLES	OLS	First stage	IV
Hemoglobin (g/dL)	0.0091***		0.0177***
	(0.0007)		(0.0048)
Sale or possession ban × beef-consumer × time dummy		-0.133***	
		(0.018)	
Cluster-level anemia prevalence 2015 × time dummy		2.700***	
		(0.046)	
Cluster FE	✓	✓	✓
Time FE	✓	✓	✓
Controls	✓	✓	✓
Observations	149,365	149,365	149,365

Notes: Standard errors clustered at the NFHS cluster-by-year level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A3. Effects of adolescent anemia on school attendance using various distance thresholds

	School enrollment			
	(1)	(2)	(3)	(4)
VARIABLES	$\alpha \leq 3$	$\alpha \leq 5$	$\alpha \leq 7$	$\alpha \leq 9$
Anemia (1=yes)	-0.056***	-0.054***	-0.038**	-0.036**
	(0.021)	(0.017)	(0.015)	(0.014)
Cluster FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	75,530	105,492	128,067	143,470

Notes: α= distance (Km). The results are based on various distance thresholds to construct a geographic panel data. Standard errors clustered at the NFHS cluster-by-year level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Effect of adolescent anemia on school enrollment– Robustness of results to various specifications

	School enrollment			
	(1)	(2)	(3)	(4)
VARIABLES	Cluster-level anemia in 2010 within 5 km radius	Cluster-level anemia in 2010 without using radius	Without cluster-level initial characteristics	State × time FE
Anemia (1=yes)	-0.044***	-0.044***	-0.039**	-0.040***
	(0.014)	(0.014)	(0.015)	(0.014)
Cluster FE	✓	✓	✓	✓
Time FE	✓	✓	✓	
Cluster-level initial characteristics × time dummy	✓	✓		✓
Controls (all)	✓	✓	✓	✓
Observations	149,313	148,947	149,365	149,365

Notes: Columns (1) and (2) include full controls similar to Column (3) of Table 1. Column (3) estimates the model without cluster-level initial year characteristics. Column (4) includes state-time fixed effects instead of time fixed effects. Standard errors clustered at the NFHS cluster-by-year level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

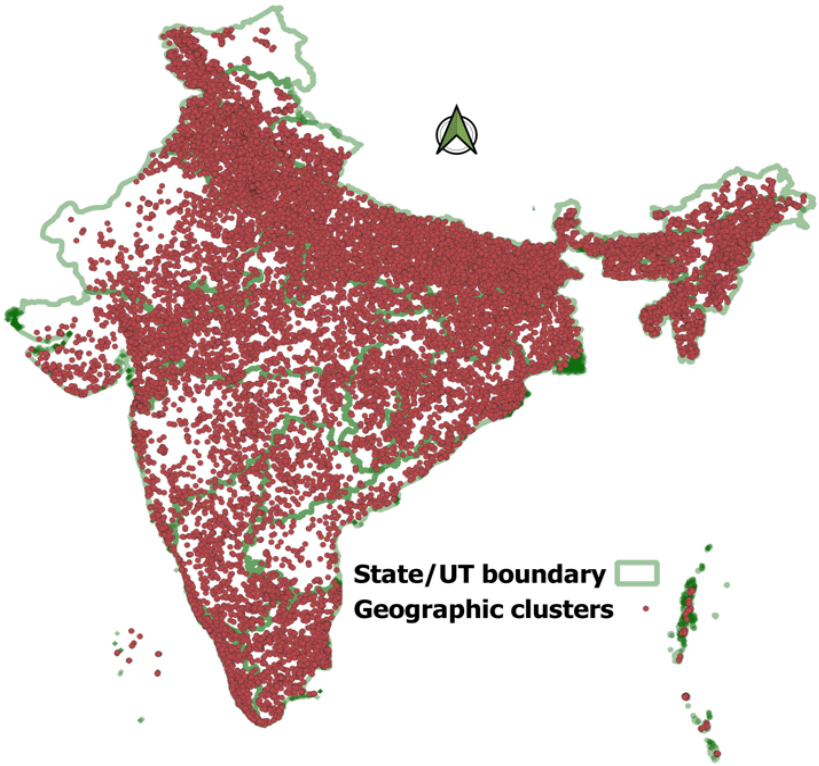


Fig.1. Study clusters in India from NFHS-4 (2015-16) and NFHS-5 (2019-21). *Source*: Author's illustration.

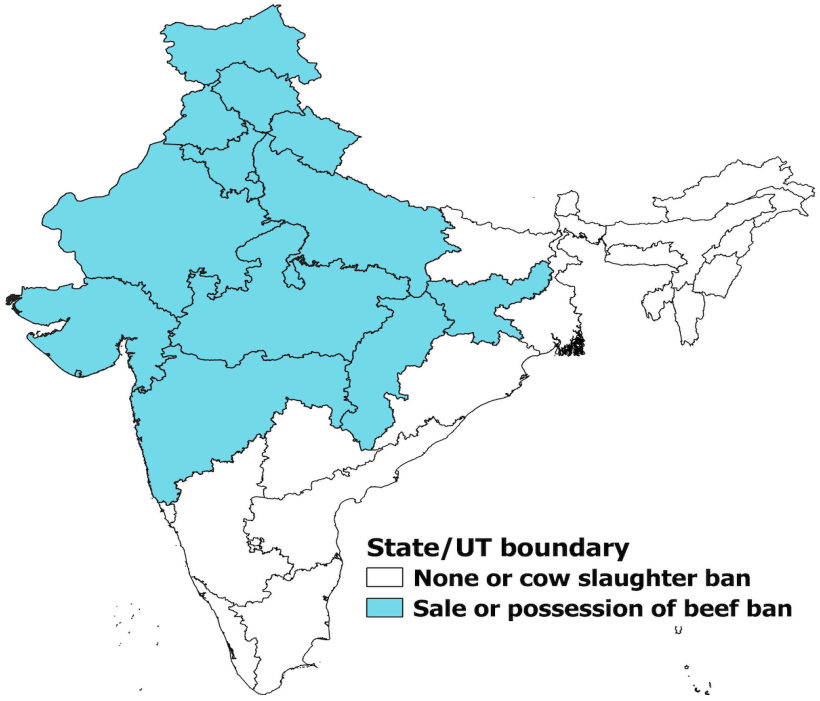


Fig.2. Sale or possession of beef ban in Indian states.
The figure shows the state/UT-level status of the possession and/or sale of beef ban in Indian states or UTs. *Source*: Dasgupta et al. (2023). Author's illustration.

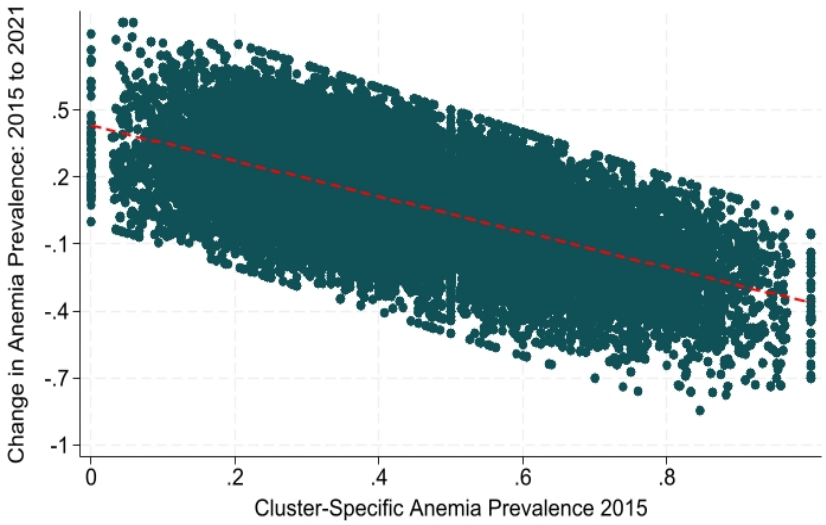


Fig. 3. Cluster-level anemia prevalence in 2015 and subsequent anemia reduction.

Notes: The figure illustrates the relationship between cluster-level anemia prevalence in 2015 and the change in anemia prevalence within clusters between 2015 and 2021.

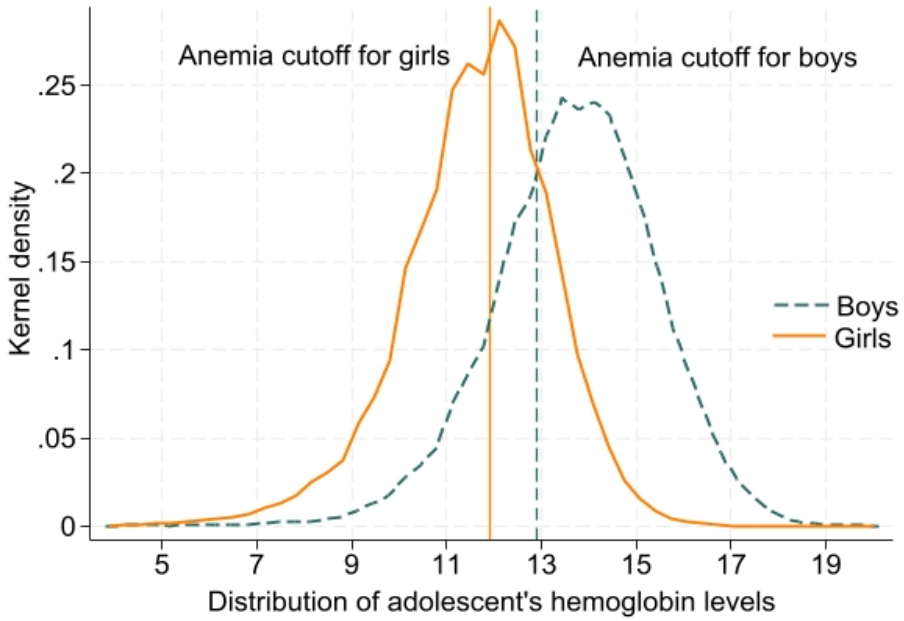


Fig. 4. Density of hemoglobin levels relative to girls' and boys' anemia cutoff. *Source*: Authors.

Online Supplementary Information

Beef ban legislation in India

India presents a unique context for this study, owing to the imposition of state-level beef ban laws and the high prevalence of anemia. In this study, we draw on the rich database compiled by Dasgupta et al. (2023), which consists of information on cattle slaughter regulations and bans on the sale or possession of beef across Indian states by state (month), year. These cattle slaughter bans were set by policy between 1950 and 2016, of which the authors reported the use of data from 1983 to 2016. The key state-level cattle slaughter ban laws data source was a report titled "Report of the National Commission on Cattle (Rashtriya Govansh Ayog), July 2002, prepared for the Department of Husbandry and Dairying, Ministry of Agriculture, Government of India (Lodha 2002). The compiled database consists of individual state-level legislations, amendments to existing laws, and subsequent legislations as summarized in the Supplementary Table S8. If a law in a state were amended, the most recent information was used from the year of the amendment. Most of the cow slaughter bans were enacted between 1950 to 1980, and since the 1980s, the legislation has mainly focused on enhancing the strictness of such bans, as some states banned the sale or possession of beef in addition to cow slaughter bans (Dasgupta et al., 2023).

Table S8: Summary of the state-level cattle slaughter ban laws in India

Year	States where new laws passed	Amendments to existing laws
1950-1955	Bombay, Bihar, Himachal Pradesh, Punjab, West Bengal, Uttar Pradesh	

1956-1976	Karnataka, Madhya Pradesh, Odisha, and Union Territories (UTs) of Andaman and Nicobar Islands and Puducherry	Gujrat newly split from Bombay, amended its law to also prohibit the slaughter of bullocks and bulls.
1976-1979	Andhra Pradesh, Goa, and Union Territories (UT) of Damana and Diu, and Dadra and Nagar Haveli	Amendments to existing laws in Himachal Pradesh and Gujrat. Himachal Pradesh increased its prison sentence and maximum fines and in Gujrat the slaughter of bullocks and bulls was permitted with a fit-for-slaughter certificate
1980-1995	Delhi in 1994 passed a cow slaughter ban and in 1995 Rajasthan imposed a cow slaughter ban	Gujrat in 1994 reinstated its ban on the slaughter of bullocks and bulls. Goa in 1995 lifted its ban and permitted the cow slaughter with a fit-for-slaughter certificate.
2000-2007	In 2000 three states were formed and passed their own laws separate from the states they were split from including: 1) Chhattisgarh (from Madhya Pradesh) in	In 2002 Uttar Pradesh increased its prison sentence and maximum fines.

	2004 imposed a ban on bullock and bull slaughter and increased the maximum fine. 2) Jharkhand (from Bihar) in 2005 lifted the ban on buffalo slaughter but imposed bans on sale and possession of beef and also raised the maximum fine and maximum and minimum prison sentence. 3) Uttarakhand (from Uttar Predesh) in 2007 imposed ban on bull slaughter and increased the maximum and minimum prison sentence and fines.	
2011-2017	In 2015 Maharashtra imposed a ban on bull slaughter and Haryana banned beef possession and both states raised maximum and minimum fines and prison sentences.	In 2011, Gujrat reinstated its ban on bull slaughter and increased its fines and prison sentence in 2017.

Source: Dasgupta et al. (2023)

Anemia Mukt Bharat (AMB) Program

The AMB program is India's flagship initiative to combat anemia. The AMB strategy was launched in 2017-18 as an intensified version of the National Iron Plus Initiative (NIPI), and it aims to achieve the POSHAN Abhiyaan (Prime Minister's scheme for Holistic Nutrition Mission) targets to reduce anemia among beneficiary groups by 3 percentage points per year. The strategy follows a "6×6×6 strategy": six beneficiary groups, six programmatic

interventions, and six institutional mechanisms to strengthen health systems (MoHFW, 2018). The six beneficiary groups include children (6-59 months), children (5-9 years), adolescents (10-19 years), lactating women, pregnant women, and women of reproductive age (15-49). The six interventions focus on both prevention and treatment of anemia, which includes – i) Prophylactic Iron and Folic Acid Supplementation (IFA), ii) Periodic deworming, iii) Intensified year-round behavior change communication campaign for – (a) compliance to IFA and deworming, (b) appropriate Infant and Young Child Feeding (IYCF), (c) increase intake of protein-rich, iron-rich, and vitamin C-rich foods, food fortification and dietary diversification, (d) promoting practice of delayed cord clamping, iv) testing and treatment of anemia using digital approaches, v) mandatory provision of IFA fortified foods in government funded health programs, and vi) intensifying awareness, screening and treatment of non-nutritional causes of anemia in endemic pockets with a particular focus on hemoglobinopathies, fluorosis, and malaria. The six institutional mechanisms aim to ensure the effective implementation of the program, which includes – i) intra-ministerial coordination, ii) convergence with other ministries, iii) national AMB unit, iv) strengthening of the supply chain and logistics, v) national center for excellence and advanced research on anemia control, vi) AMB dashboard and digital portal-one-stop shop for anemia (www.anemiamuktbharat.info).

Under the AMB IFA supplementation intervention, pregnant and lactating women are provided with IFA blue tablets, and adolescent girls and boys are provided with IFA blue tablets. The children (6-59 months) are provided with IFA syrup, while children (5-9 years) are provided with IFA pink tablets. The composition and dosage of IFA are mentioned in the AMB operational guidelines. The dashboard provides an AMB index – an average of the IFA supplementation coverage among beneficiary groups. This information is used to generate a

state-level AMB ranking from its annual scorecard. This scorecard presents the performance metrics for IFA coverage across Indian states and UTs, based on the data from the Health Management Information System (HMIS) and AMB dashboard.

Table S1: Effect of adolescent anemia on school enrollment

	School enrollment	
	(1)	(2)
VARIABLES	Possession or sale ban × beef consumer × time dummy	Cluster-level anemia prevalence 2015 × time dummy
Anemia (1=yes)	-1.321***	-0.031**
	(0.321)	(0.014)
Controls	✓	✓
Observations	149,365	149,365

Notes: IV estimates are reported for both instruments, separately. Standard errors clustered at the NFHS cluster-by-year level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table S2. Reduced-form results on the relationship between school enrollment and instruments

	School enrollment	
VARIABLES	(1)	(2)
Possession or sale ban x beef-consumer × time dummy	-0.081***	-0.037***
	(0.005)	(0.005)
Cluster-level anemia 2015 × time dummy	0.031**	0.028**
	(0.012)	(0.013)
Cluster FE	✓	✓
Time FE	✓	✓
Controls		✓
Observations	149,365	149,365

Notes: Standard errors clustered at the NFHS cluster-by-year level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table S3: Effect of adolescent anemia on school enrollment

	Anemia	
VARIABLES	(1)	(2)
Panel A: First-Stage Estimation		
Beef ban × beef consumer × time dummy	0.015***	0.017***
	(0.004)	(0.004)
Cluster anemia prevalence 2015 × time dummy	-0.858***	-0.903***
	(0.012)	(0.013)
	School enrollment	
Panel B: Second-Stage Estimation		
Anemia (1= yes)	-0.053***	-0.042***
	(0.014)	(0.014)
Cluster FE	✓	✓
Time FE	✓	✓
Cluster-level controls		✓
Household controls		✓
Individual controls		✓
Mean of the dependent variable	0.688	0.688
Observations	149,365	149,365

Notes: Table reports main results similar to Table 1 using any beef ban × beef-consumer × time dummy as an IV instead of possession or sale ban × beef-consumer × time dummy. The beef ban here refers to the cow slaughter ban in Indian states by 2016. Standard errors clustered at the NFHS cluster-by-year level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table S4. Association between adolescents' gender and intra-household food allocation behaviour

VARIABLES	Meat or chicken	Fish	Eggs	Fruits	Pulses or beans	Dark green vegetables
	(1)	(2)	(3)	(4)	(5)	(6)
Male adolescent	0.075***	0.060***	0.094***	0.050***	-0.024***	-0.0006
	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.007)
Controls	✓	✓	✓	✓	✓	✓

Notes: n=146,767. The binary indicators are used in column headers. Each variable is coded as 1 if the food item is consumed daily or weekly and 0 if the food item is never or occasionally consumed. Standard errors clustered at the NFHS cluster-by-year level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table S5. Effect of anemia on school enrollment by the structure of the household

	School enrollment	
	(1)	(2)
VARIABLES	Nuclear family	Non-nuclear family
Anemia (1=yes)	-0.037*	-0.076***
	(0.020)	(0.025)
Controls (all)	✓	✓
Observations	81,202	64,411

Notes: Standard errors clustered at the NFHS cluster-by-year level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table S6. Effect of anemia on school enrollment by AMB index quintile (State-level IFA supplements coverage)

	School enrollment		
	(1)	(2)	(3)
VARIABLES	AMB index low	AMB index medium	AMB index high
Anemia (1=yes)	-0.059*	-0.031	-0.060**
	(0.029)	(0.022)	(0.025)
Cluster FE	✓	✓	✓
Time FE	✓	✓	✓
Controls	✓	✓	✓
Observations	44,491	48,773	56,101

Notes: IV estimates are based on three equal quintiles. Standard errors clustered at the NFHS cluster by year level is reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table S7: Effect of anemia on current school attendance by AMB index dummy (State-level IFA coverage)

	School enrollment	
	(1)	(2)
VARIABLES	AMB index low	AMB index high
Anemia (1=yes)	-0.064***	-0.033
	(0.017)	(0.025)
Controls	✓	✓
Observations	95,452	53,913

Notes: The AMB index score is coded as 1 (high) if the index score is above the median value of 28.35; otherwise, it is coded as 0 (low). Standard errors clustered at the NFHS cluster-by-year level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table S8: Effect of anemia on current school enrollment depending on anemia intensity

	School enrollment					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Anemia (1= yes)	-0.052***	-0.042***				
	(0.014)	(0.014)				
Anemia (moderate)			-0.107***	-0.084***		
			(0.024)	(0.025)		
Anemia (severe)					-1.432***	-1.143***
					(0.283)	(0.285)
Controls	✓	✓	✓	✓	✓	✓
Observations	149,365	149,365	149,365	149,365	149,365	149,365

Standard errors clustered at the NFHS cluster-by-year level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table S9: T-test statistics for time-invariant characteristics of geographic panel clusters

	(1)		(2)		(1)-(2)
	Round 2015		Round 2021		Pairwise *t-test*
Variable	N	Mean/(SE)	N	Mean/(SE)	Mean difference
Proportion of households with native language Hindi	17,946	0.495	17,946	0.490	0.005
		(0.004)		(0.004)	
Cluster's altitude	17,946	371.323	17,946	371.078	0.244
		(3.533)		(3.540)	
Distance of cluster to district centroid (Km)	17,946	23.798	17,946	23.769	0.029
		(0.102)		(0.102)	

Notes: Table reports *t*-test statistics for mean differences of time-invariant cluster-level characteristics using NFHS-4 and NFHS-5 matched clusters. *** p<0.01, ** p<0.05, * p<0.1.

Table S10: Relationship between IV (Sale or possession ban × beef-consumer × time dummy) and food consumption indicators

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Any meat	Fish	Eggs	Green vegetables	Pulses and beans
Sale or possession ban × beef-consumer × time dummy	0.0455***	0.0521***	0.0697***	0.0274***	0.0044
	(0.0047)	(0.0043)	(0.0052)	(0.0039)	(0.0035)
Cluster FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Observations	146,753	146,753	146,753	146,753	146,753

Notes: Any meat includes the consumption of chicken or any other meat. Standard errors clustered at the NFHS cluster-by-year level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table S11: Effect of adolescent anemia on school enrollment (with and without chicken or any meat consumption

	Anemia	School enrollment	
	(1)	(2)	(3)
VARIABLES	OLS	IV	IV
Anemia (1= yes)		-0.033**	-0.040***
		(0.014)	(0.014)
Consume chicken or meat (daily or weekly)	-0.008*	-0.092***	
	(0.004)	(0.004)	
Consume chicken or meat (occasionally)	-0.003	-0.098***	
	(0.004)	(0.003)	
Cluster FE	✓	✓	✓
Time FE	✓	✓	✓
Controls	✓	✓	✓
Observations	146,753	146,753	146,753

Notes: Standard errors are clustered at the NFHS cluster-by-year level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table S12: Effect of adolescent anemia on school enrollment (with and without blood transfusion)

	Anemia	School enrollment	
	(1)	(2)	(3)
VARIABLES	OLS	IV	IV
Anemia (1= yes)		-0.040**	-0.040***
		(0.014)	(0.014)
Had blood transfusion in the past (1=yes)	0.033***	-0.008	
	(0.009)	(0.008)	
Cluster FE	✓	✓	✓
Time FE	✓	✓	✓
Controls	✓	✓	✓
Observations	146,753	146,753	146,753

Notes: Standard errors clustered at the NFHS cluster-by-year level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

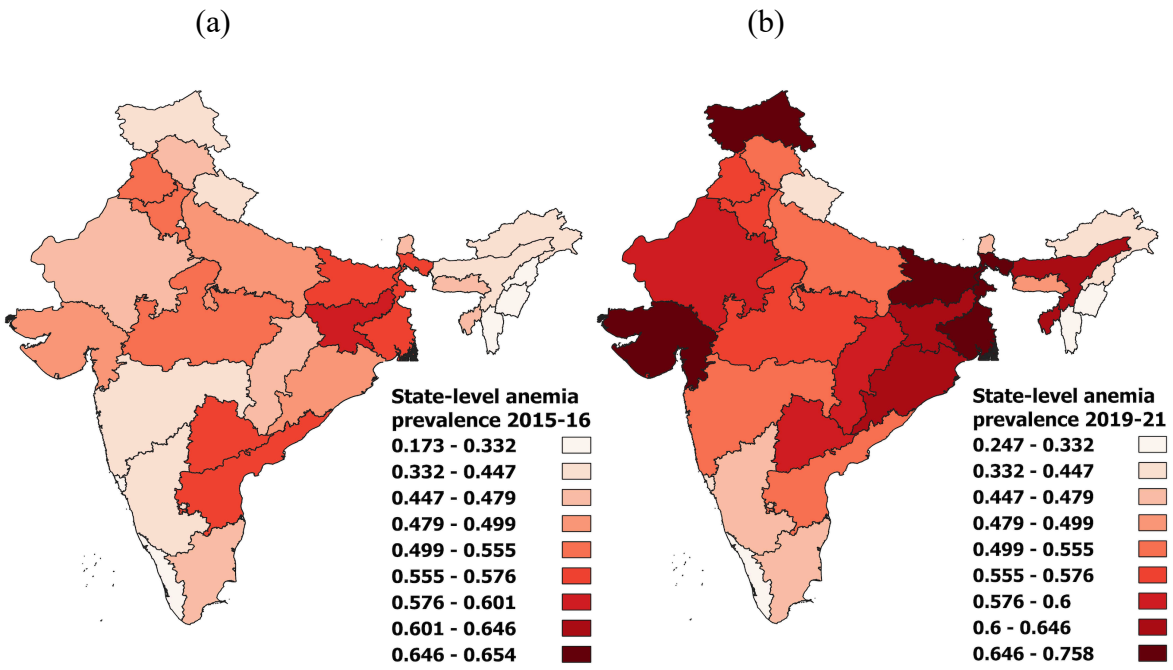


Fig. S1. State-level adolescent anemia prevalence in 2015-16 and 2019-21, based on the study sample from NFHS-4 and NFHS-5.

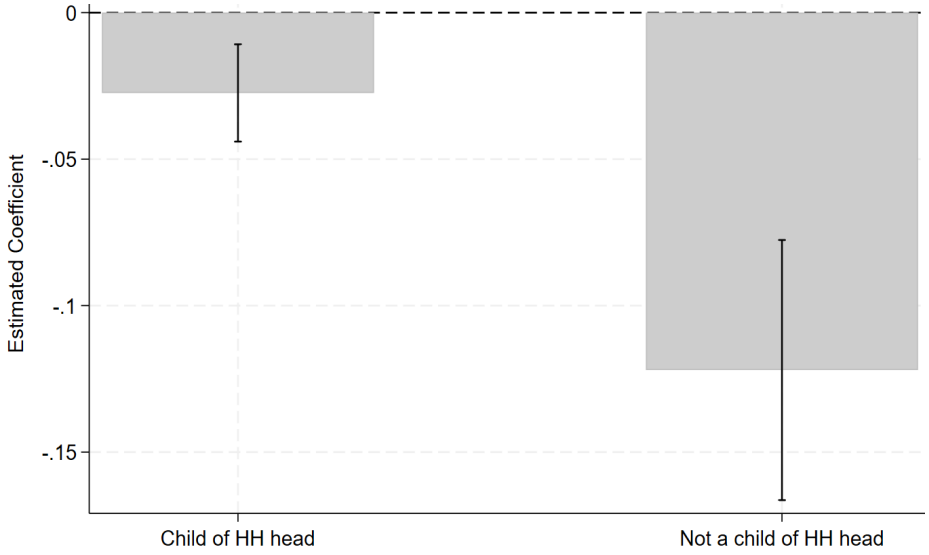


Fig. S2. Effect of adolescent anemia on school enrollment by the relationship to the household head. *Source*: Authors.

References

Dasgupta, A., Majid, F., & Orman, W. H. (2023). The nutritional cost of beef bans in India. Journal of Development Economics, 163, 103104. https://doi.org/10.1016/j.jdeveco.2023.103104

Ministry of Health and Family Welfare (MoHFW) (2018). *Anemia Mukt Bharat Dashboard*. Accessed July 26, 25, https://anemiamuktbharat.info/resources/home#AMB%20Score%20Cards.