The Cognitive Costs of Early Life Nutrition Shocks: Evidence From Beef Bans in India

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Abstract

We examine the developmental consequences of state-level beef prohibition laws in India—which criminalize the sale or possession of beef—by estimating their long-term effects on children's learning outcomes. These laws disproportionately affect religious minorities and lower-caste Hindus for whom beef is a culturally acceptable and affordable source of iron. We combine state-level ban data that we compiled from original sources (including state gazettes) with nationally representative rural schooling and test-score data from ASER (1,975,247 observations) and Census data of religion and caste proportions at the district level. Using a triple-difference design, we exploit variation in the timing of beef bans, children's birth cohorts, and district-level beef consumption intensity. We find that children born in districts with a higher-than-average proportion of beef consumers, who were exposed to beef bans in early childhood, score significantly lower in reading and math: 0.071 and 0.084 standard deviations, respectively. We also document an increase in the likelihood of being out of school in the affected districts. These effects are consistent with mechanisms operating through early-life iron deficiency and reduced educational participation. Our findings highlight how identity-based regulations—though framed as symbolic or moral—can impose persistent developmental costs on marginalized communities, and shape the inter-generational transmission of disadvantage.

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1 Introduction

Religious beliefs and cultural norms shape economic life in profound ways, from daily consumption habits to national policies. When states legislate religious norms – whether to promote symbolic identity or enforce moral codes – they may generate unintended economic consequences. One common but understudied domain is diet: across the world, governments regulate food production and consumption in line with religious or cultural principles. Yet little is known about how such policies affect long-term human development. This paper asks whether religious dietary laws, when codified into state policy, can influence early-life nutrition, schooling, and cognitive development.

We study this question in the context of India, where beef bans have proliferated across states over the past two decades. These laws, typically prohibiting the sale or possession of beef, are rooted in Hindu religious norms that view the cow as sacred. While promoted as expressions of cultural morality, such bans directly constrain the diets of religious minorities and lower-caste Hindus, most notably Muslims, Christians, and Scheduled Castes (SCs), for whom beef is a historically important and affordable source of iron and protein Ferry (2020).

India's children face acute developmental challenges by global standards (Soni et al., 2021). School enrollment in India among children aged 6–14 exceeds 95%, yet learning deficits remain stark: nearly half of rural grade 5 students cannot read a grade 2 text, and fewer than one-third can perform basic division (Muralidharan and Singh, 2021). On the PISA international assessment, Indian students scored well below average in foundational math and reading skills in 2009, the only year Indian students were tested (Walker, 2011). Domestic surveys such as ASER similarly document widespread learning deficits, especially among marginalized groups (Shah and Steinberg, 2021). At the same time, India has among the highest rates of anemia in the world, with over half of all women and children suffering from iron deficiency (Balarajan et al., 2013). These dual burdens – nutritional deprivation and poor learning outcomes – are concentrated among low-income and minority populations, and they pose serious long-term constraints on human capital formation. If beef bans further reduce access to iron-rich diets and indirectly affect schooling behavior, they may reinforce intergenerational disadvantage in subtle but persistent ways.

In this paper, we ask whether beef bans affect children's cognitive development, particularly in regions where beef is a dietary staple. We hypothesize that beef bans impose a developmental burden by exacerbating early-life iron deficiency during critical periods of brain development. This in turn can affect schooling behavior and investments. These effects are likely to be concentrated in districts where beef consumers are most prevalent and

among households that lack access to nutritional substitutes.

We test this hypothesis using a novel panel dataset that combines several sources. First, we use child-level data from the Annual Status of Education Report (ASER), a nationally representative survey of rural children's math and reading outcomes, designed to be representative at the rural district level (Banerji et al., 2013). Second, we collect and harmonize legal records on the timing of beef ban legislation across states. Third, we incorporate district-level data from the 2011 Census on the share of Muslim, Christian, and Scheduled Caste households (likely beef consumers), which proxies for the salience of beef as a nutritional input. Using children's year of birth, we construct exposure to beef bans in one's birth year (peri-natal), a critical period of development, based on the timing of state-level implementation.

Our identification strategy uses a triple-difference (DDD) design that exploits three sources of variation: (i) the staggered rollout of beef bans across states, (ii) children's birth cohorts (defining early-life exposure), and (iii) district-level differences in beef consumption intensity. We compare test scores of children born before and after bans, across high- and low–beef-consuming districts, and in states with and without bans. All regressions include fixed effects for state, birth year, and state-by-birth year, and control for child gender, household wealth, and survey year. Our main outcomes are age-adjusted z-scores in math and reading. Our coefficient of interest is the interaction between the beef ban indicator and a binary indicator for whether a district has an above-average share of beef-consuming households.

We find that beef bans significantly reduce cognitive outcomes, as measured by ASER test scores, in districts where beef is commonly consumed. Specifically, children born in high beef-consuming districts under beef bans score 0.084 standard deviations lower in math and 0.071 standard deviations lower in reading compared to children born in similar districts without bans. These effects are statistically significant at the 10 percent level, based on wild cluster bootstrap p-values clustered at the state level. The findings suggest that state-imposed dietary restrictions can impose persistent cognitive penalties on nutritionally vulnerable populations.

To investigate mechanisms, we draw on prior work showing that beef bans increase rates of maternal anemia among beef-consuming groups. Anemia during pregnancy is a known risk factor for impaired fetal brain development, low birth weight, and lower schooling attainment (Basu et al., 2018; Rahmati et al., 2017; Fararouei et al., 2010). Consistent with this biological channel, we interpret our results as reflecting early-life nutritional deprivation. In addition,

we document effects on educational investments: beef bans are associated with a statistically significant increase in the likelihood that children are out of school in high beef-consuming districts. This suggests a second channel through which beef bans may worsen cognitive outcomes: by discouraging school participation in affected communities.

This paper contributes to several strands of literature. First, we extend research on the developmental origins of inequality by showing how religiously motivated policy can alter early-life human capital trajectories. Second, we contribute to the literature on nutrition and cognition by identifying a plausibly exogenous policy shock, beef sale and possession bans, that alters access to heme iron in a large, diverse population. Third, we speak to the broader debates in political economy and law about the distributional consequences of majoritarian cultural regulation. While beef bans are typically framed as symbolic or moral legislation, our findings show that they carry real and unequal developmental costs, particularly for historically marginalized groups.

More broadly, our results underscore the unintended consequences of identity-based policymaking. As more governments legislate religious or cultural norms, it is critical to assess not just their symbolic value but also their developmental spillovers. In this case, a dietary law aimed at moral conformity generates tangible cognitive and learning losses among children in disadvantaged communities.

2 Institutional Context and Conceptual Framework

2.1 Religious Diet Laws and the Rise of Beef Bans

We collect and assemble legislation using state gazettes from 26 Indian states in both Hindi and English, along with federal documents, to compile a historical state-level panel data set on legislation banning the slaughter of cattle and the sale or possession of beef, between 1950 and 2018 by state and month-year. For the historical context of the bans, and for the details of the construction of the data set, please see the Data Appendix in Dasgupta et al. (2023).

Of the 28 states in India, seven have no cattle slaughter bans. Of the remaining, eleven also criminalize either the sale or possession of beef, or both. These bans were adopted across states at different times. During our sample period, which spans children born between 1996 and 2013, two states with cattle slaughter bans added both beef sale and possession bans: Jharkhand in 2005, and Gujarat in 2011. Since Muslims, Christians, and Hindus belonging to Scheduled Castes typically consume beef, while other religious and caste groups typically do not, we expect them to be affected by these bans, while the other groups serve as a

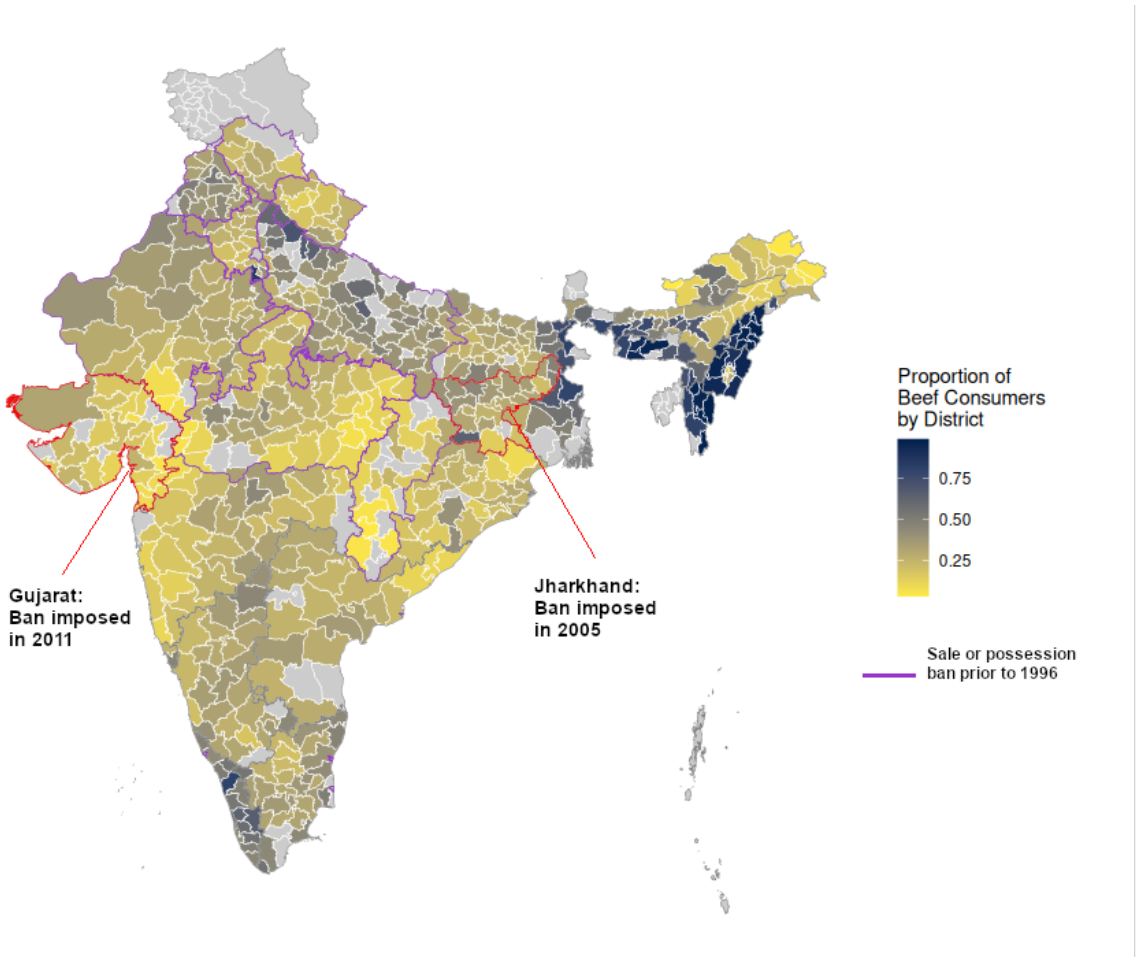


Figure 1: Proportion of Beef Consumers by District (2011 Census)

control group (Ferry, 2020). We define the proportion of beef consumers in a district as the sum of the proportions of Muslims, Christians, and Scheduled Caste Hindus in the district population as per the 2011 Census. Figure 1 shows the proportion of beef consumers by district, with state border colors indicating the status of beef bans. Religion and dietary choices are a polarizing and politically charged topic in India, and "cow protection vigilantes" receive wide coverage in both traditional and social media (Farooq, 2022).

Conceptual Framework

In places where beef is a regular staple, beef bans remove an affordable source of highly bioavailable heme iron, raising maternal anemia risk, disrupting fetal brain development, and ultimately lowering children's human capital as reflected in test scores and schooling outcomes. This fits the broader fetal origins literature showing that even relatively mild prenatal shocks can have persistent impacts on human capital (Almond and Mazumder,

2011; Almond et al., 2015; Majid, 2015). In the Indian context, prior work finds that beef bans increased maternal anemia (Dasgupta et al., 2023).

Heme iron from meat is absorbed substantially better than non-heme iron from plants (Hallberg and Hulthén, 2000; Hunt, 2003; Zimmermann and Hurrell, 2007). Common Indian staple foods such as cereals and legumes are high in phytates and polyphenols that inhibit non-heme iron absorption, and widely consumed beverages like tea further depress absorption (Hurrell et al., 1999; Hurrell and Egli, 2010; Thankachan et al., 2008). Given India's largely cereal- and pulse-based diets (Deaton and Drèze, 2009), merely substituting plants for lost meat is biologically an imperfect substitute, so that removing a low-cost heme-iron source plausibly raises anemia risk among pregnant women in beef-consuming communities.

The first 1,000 days (conception–age 2) are a period of rapid brain growth and organization (Cusick and Georgieff, 2016). Iron supports myelination, hippocampal development, neurotransmitter synthesis, and energy metabolism; iron-deficiency anemia in pregnancy can alter brain structure and function in utero, with effects that may persist even after later repletion (Georgieff, 2008; Lozoff and Georgieff, 2006; Georgieff, 2020). Low maternal iron intake is linked to altered neonatal brain structure (Monk et al., 2016), and registry evidence ties first and second trimester anemia to higher risks of ASD/ADHD (Wiegersma et al., 2019). Systematic reviews document that maternal iron status during pregnancy is associated with offspring cognition, academic achievement, and behavior (Janbek et al., 2019; Quezada-Pinedo et al., 2021). A large Spanish cohort reports higher working memory/executive function at age 7 when first-trimester ferritin exceeded 12 μg/L (Arija et al., 2019).

Systematic evidence (including from South Asia) shows poorer maternal iron status predicts lower cord hemoglobin and higher neonatal/infant anemia (Zhao et al., 2024). Indian cohort data similarly document strong maternal–child hemoglobin gradients in the first 2–3 years, indicating prenatal shocks carry forward into early childhood (Heesemann et al., 2021).

Randomized trials and meta-analyses in low and middle-income countries (LMICs) show that improving child iron status raises standardized cognitive performance as measured by IQ or global cognition, attention, and working memory (Falkingham et al., 2010; Murray-Kolb, 2011). In India, a randomized feeding trial of iron-biofortified pearl millet improved iron status and attention/memory task performance among adolescents (Scott et al., 2018; Finkelstein et al., 2015).

In high-deficiency settings, maternal supplementation shows later-child benefits. In Indonesia, children of mothers randomized to multiple micronutrients including iron scored

higher at ages 9–12, with larger gains when mothers were anemic at baseline (Prado et al., 2017). In rural Nepal, antenatal iron–folic acid was associated with higher general intelligence and components of executive/fine-motor function at ages 7–9 (Christian et al., 2010). These findings are exactly what the biology predicts and are most pronounced where baseline deficiency is high.

Standardized achievement tests reflect both cognitive and non-cognitive skills (attention, self-regulation, motivation). Maternal anemia is associated with higher risks of early developmental/behavioral problems (Wiegersma et al., 2019), and early cognitive delays predict poorer school outcomes and increased dropout (Behrman et al., 2004; Glewwe et al., 2011; Currie and Thomas, 2001). Together, this implies measurable effects on test scores, not only on narrow IQ measures.

Our mechanism sits under the same predictive adaptive response (PAR) umbrella as the Ramadan literature: prenatal shocks produce lasting cognitive and behavioral effects. Ramadan studies emphasize a stress–endocrine channel in which maternal circadian fasting elevates cortisol and alters placental development, plausibly affecting the fetal hypothalamic-pituitary-adrenal (HPA) axis and later academic performance (Almond et al., 2015; van Ewijk, 2011; Dikensoy et al., 2009; Alwasel et al., 2010; Gluckman and Hanson, 2005). We build on that precedent, but focus on a distinct nutritional channel: policy-driven withdrawal of heme iron induces higher maternal anemia, which in turn leads to impaired fetal neurodevelopment and lower later test performance. The channels are complementary, not competing.

Maternal anemia can directly depress later test scores. It can do so via direct in-utero effects on fetal brain development—even if a study does not detect changes in the child's postnatal iron status. As discussed above, iron deficiency during pregnancy alters brain structure and function in the first 1,000 days, and prenatal supplementation trials in high-deficiency settings show downstream gains in cognition when maternal iron/micronutrient status improves—evidence consistent with an in-utero pathway that need not operate solely through postnatal child anemia (Georgieff, 2008; Monk et al., 2016; Christian et al., 2010; Prado et al., 2017). Accordingly, our identification does not hinge on observing effects on child anemia to justify impacts on test scores, even though a complementary maternal-to-child anemia transmission channel is also plausible (Zhao et al., 2024).

Given high baseline levels of anemia and the prevalence of dietary inhibitors of non–heme iron in India (Natekar et al., 2022), beef bans plausibly depress children's later school performance (test scores, grade progression, and dropout) via the maternal–anemia channel, with

additional feedback to achievement through behavior and school participation. These implications are consistent with evidence from neurobiology, cohort studies, LMIC meta-analyses, and South-Asia–specific randomized interventions, and may hold even when changes in postnatal child anemia are small or undetected.

3 Data and Empirical Strategy

3.1 Data

For the details of cattle slaughter and beef sale and possession bans, we use our constructed panel data set on state-level legislation between 1950 and 2018 by state and month-year (for the historical context of the bans, and for the details of the construction of the data set, please see the Data Appendix in Dasgupta et al. (2023)).

For schooling and learning outcomes, we use the Annual Status of Education Report (ASER) for the years 2012, 2014, 2016, and 2018. The ASER survey, conducted annually since 2005, measures schooling and learning outcomes for children aged 5-16. It is a representative household level survey, which covers all rural districts in India. We use data on children ages 5-16, for a total of 1,975,247 observations over the four years. Unlike many other datasets on test scores, children are surveyed at home, which means that data is available regardless of a child's school enrollment status. The ASER data also contains data on the child's age, sex, household assets such as the type of house and appliances present (which we use to compute a wealth index), language of instruction at the child's school, school type.

Children were tested on their ability to read in their language of instruction, as well as their basic math ability. Scores are coded as a number from 1-5, where 1 indicates the lowest and 5 the highest score. See Table 1 for details on how scores were assigned.

Table 1: Assignment of ASER Reading and Math Scores

Score	**Reading**	**Math**
	Child can:	
1	Not read anything	Not do any arithmetic
2	Identify letters	Recognize numbers 1–9
3	Read words	Recognize numbers 11–99
4	Read a first grade level sentence	Do two-digit subtraction
5	Read a second grade level paragraph	Do division (3-by-1 form)

We convert each of these codes into z-scores by the child's age, comparing each child's learning level to other children their age.

The ASER data shows the extent of learning deficits among children in rural India. Figure 2 shows that even by age 16, about 20% of children cannot read a second grade level paragraph, and and almost half cannot solve a 3-digit by 1-digit division problem. Fewer than a third of 8 and 9 year-old children are able to read at a second grade level.

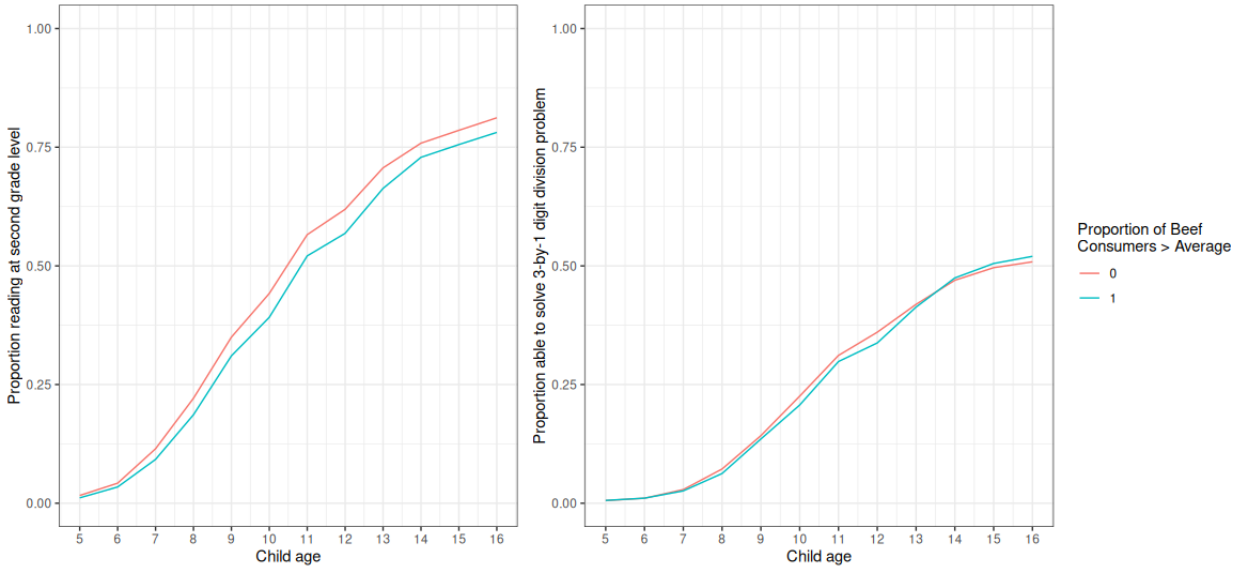


Figure 2: Proportion of children with test scores at the highest level, by age and proportion of beef consumers in the district

We use the 2011 Census of India to obtain district-level populations by religion, and the 2011 Socioeconomic and Caste Census of India to obtain district-level populations by caste. The 2011 Census is the most recent comprehensive national-level data available.

3.2 Treatment and Exposure

We assign a policy variable $\text{Ban}_{sb} = 1$ if state s had a ban on the sale or possession of beef in effect during child's birth year b. We assign an exposure variable $\text{Exposure}_d = 1$ if the population of district d has a proportion of beef consuming groups greater than the national mean, as measured using 2011 Census data. This district-level variable is time-invariant; we believe this is justified by stable religious dietary patterns over time, and relatively low migration in India relative to other developing countries (Munshi and Rosenzweig, 2016).

3.3 Raw mean differences, double differences, and triple differences

Figure 3 presents the raw mean difference in math Z-scores (exposed at birth minus not exposed) for Jharkand versus states that were never exposed to beef sale or possession bans.

In the high-beef consumption districts (blue bars), the gap is 0.000 SD in the never-treated states versus –0.228 SD in Jharkhand, yielding a difference-in-differences (DID) of –0.228 SD. In the low-beef districts (grey bars), the corresponding DID is –0.126 SD. The triple-difference (DDD) between these two DIDs is –0.102 SD.

Figure 5 shows the same calculation for Jharkhand's reading Z-scores: in high-beef areas the DID is –0.161 SD, and in low-beef areas it is –0.043 SD, for a DDD of –0.118 SD. These descriptive patterns suggest that exposure at birth to beef bans is associated with lower early-life test scores, with a larger penalty in districts with higher pre-ban beef consumption.

When we repeat this exercise for Gujarat (Figure 4), we again observe negative triple-difference estimate, although its magnitude is much smaller than in Jharkhand for math. Because no Gujarat districts exceeded the national average beef-consumption threshold (which we used to define high vs low beef costumer districts in general) , we defined "high-beef" and "low-beef" districts relative to Gujarat's own mean consumption. This within-state classification may introduce additional measurement error when comparing across contexts with different consumption norms.

Figure 6 shows the reading Z-score findings for Gujarat: the DID estimates are –0.094 SD (high-beef) and +0.056 SD (low-beef), for a DDD of –0.149 SD. These estimates are larger not only than math, but also compared to Jharkhand's reading scores. We study these differences more formally in the regression framework in the Results section.

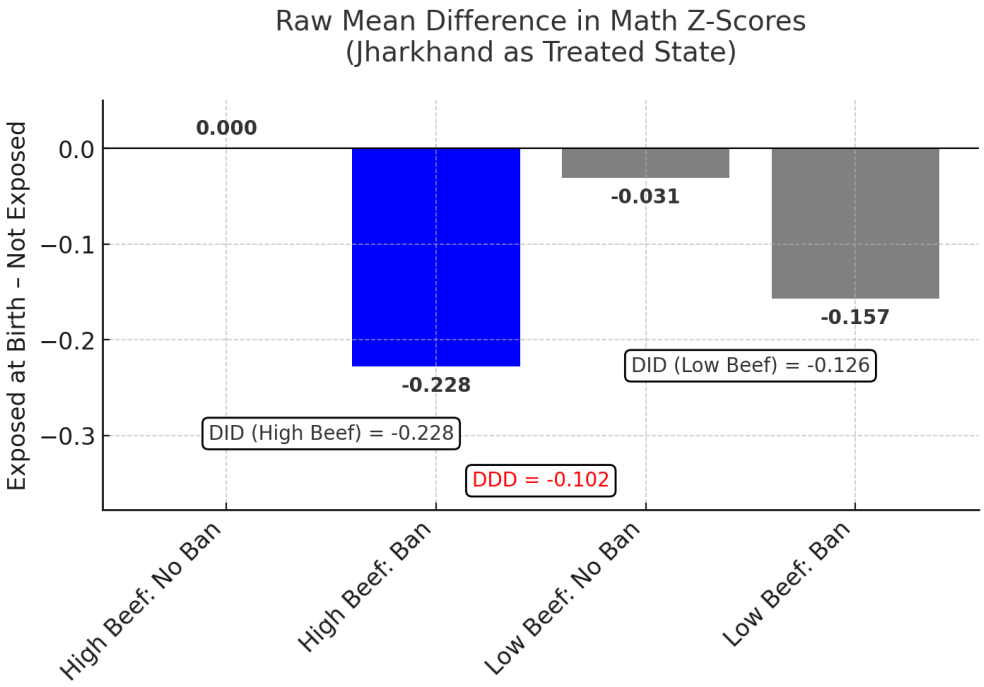


Figure 3: Raw Mean Differences in Math Z-Scores (Jharkhand).

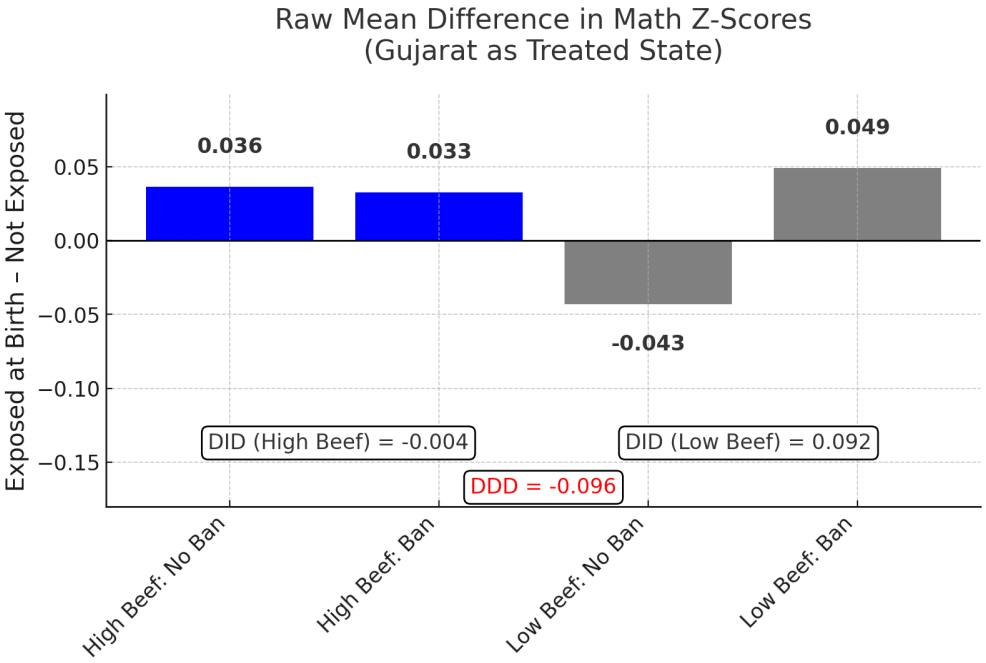


Figure 4: Raw Mean Differences in Math Z-Scores (Gujarat).

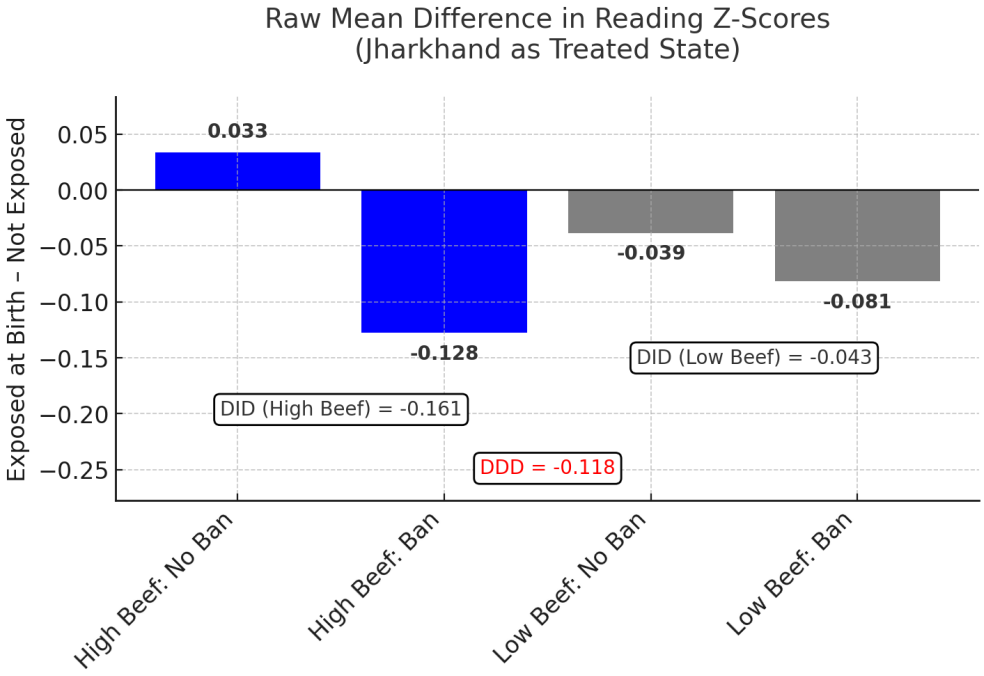


Figure 5: Raw Mean Differences in Reading Z-Scores (Jharkhand)

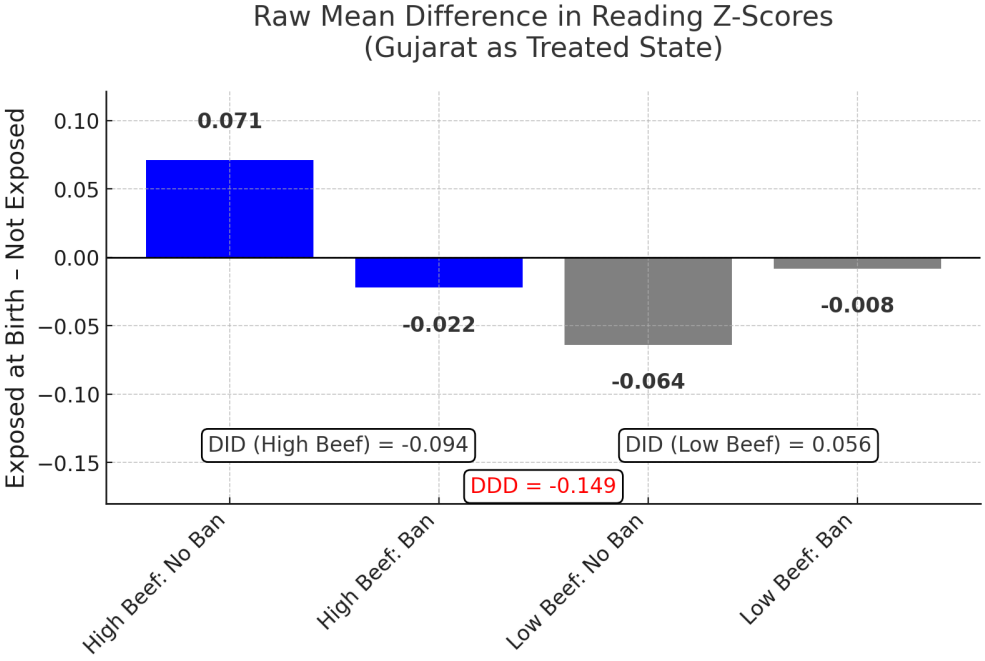


Figure 6: Raw Mean Differences in Reading Z-Scores (Gujarat)

3.4 Estimation Strategy

Our identification strategy employs a triple difference-in-differences model using three sources of variation:(i) the staggered rollout of beef sale or possession ban laws across states in India. (ii) birth cohort-level variation for children exposed to these bans, and (iii) district-level differences in beef consumer proportion intensity. We use alternate definitions of high intensity of beef consumers: (i) the sum of the proportions of Muslims, Christians and Scheduled Caste Hindus in a district, and (ii) an indicator variable which equals 1 if the proportion of beef consumers in the district is higher than the national mean district-level proportion of beef consumers, and 0 otherwise.

$$Y_{isdb} = \alpha + \beta_1 \text{Ban}_{sb} + \beta_2 \text{Exposure}_d + \beta_3 (\text{Ban}_{sb} \times \text{Exposure}_d) \ + \lambda sb + \delta_y + X'_{isdb}\gamma + \varepsilon_{isdb}$$

Y: Math, reading, or composite test score, or school participation outcome for child i in state s from district d and born in year b. The composite achievement score standardizes reading and mathematics scores to z-scores (mean 0, sd 1) within the analysis sample and take their row mean average. This yields an index in standard-deviation units, consistent with Kling et al. (2007), Anderson (2008), and Hoynes et al. (2016).
λ_{sb}: State $\times$ birth cohort fixed effects
δ_y: Survey year fixed effects
Standard errors are clustered at the state level, using wild bootstrap clustering.

β_3 is the parameter of interest which estimates the treatment effect of beef bans on learning outcomes for children by comparing cohorts, before and after the bans, in high-versus-low beef consumption districts. We control for State $\times$ birth cohort fixed effects, survey year fixed effect, and an array of demographic characteristics such as child age, household wealth, gender and survey year. The State $\times$ birth cohort fixed effects control for all state-level policy variation over time.

Our identification strategy relies on district-level proportions of beef consumers being independent of state-level policy variation. We are unable to interact the beef consumer proportion or indicator variable with state or time, since it is time-invariant – we only have population data from the 2011 Census.

Table 2: Triple-Difference Estimates: Effect of Beef Bans × Beef Consumers on Test Scores

	Composite Score	Reading Score	Math Score
Beef Ban × Beef Consumers	-0.077	-0.071	-0.084
	(0.038)	(0.035)	(0.044)
Observations	1,422,170	1,420,308	1,417,873
Bootstrap p-value	0.050	0.039	0.085

Notes: This table reports triple-difference (DDD) estimates of the interaction between beef bans and district-level beef consumption on children's test scores. Standard errors (in parentheses) are clustered at the state level. Reported p-values are obtained from wild cluster bootstrap. All models include controls for child age, gender, household wealth, and year fixed effects.

3.5 Results: Test Scores

Table 2 reports the triple-difference estimates of the interaction between beef bans and district-level prevalence of beef-consuming groups on children's test scores. We find that exposure to beef bans in high–beef-consuming districts is associated with a statistically and economically meaningful reduction in cognitive performance. Specifically, children born in affected districts score 0.077 standard deviations lower on the composite test score index, 0.071 standard deviations lower in reading, and 0.084 standard deviations lower in math, relative to children in low–beef-consuming districts or in periods without bans. Bootstrap p-values indicate that these effects are statistically significant at conventional levels for the composite and reading outcomes and marginally significant for math. These results are robust to the inclusion of controls for child age, gender, household wealth, and survey year fixed effects, and the standard errors are clustered at the state level. Taken together, these findings suggest that beef bans—by limiting access to an affordable and iron-rich food source—may hinder early-life nutrition and consequently reduce children's cognitive development.

3.5.1 Test Scores by Gender

Table 3 presents triple-difference estimates separately for female (Panel A) and male (Panel B) children. The estimated effects are similar across genders: for girls, exposure to beef bans in high–beef-consuming districts is associated with a 0.071 standard deviation reduction in composite test scores, compared to a 0.083 standard deviation reduction for boys. The pattern is consistent across reading and math scores, with slightly larger point estimates for boys; however, the bootstrap p-values indicate that these differences are not statistically distinguishable. Taken together, these results suggest that the adverse cognitive effects of beef bans are broadly comparable for male and female children, implying that the underlying

Table 3: Triple-Difference Estimates: Effect of Beef Bans × Beef Consumers on Test Scores, by Gender

	Composite Score	Reading Score	Math Score
Panel A: Female Children			
Beef Ban × Beef Consumers	-0.071	-0.061	-0.081
	(0.041)	(0.039)	(0.045)
Observations	697,602	696,710	695,437
Bootstrap p-value	0.067	0.070	0.098
Panel B: Male Children			
Beef Ban × Beef Consumers	-0.083	-0.079	-0.087
	(0.040)	(0.038)	(0.043)
Observations	724,568	723,598	722,436
Bootstrap p-value	0.052	0.043	0.081

Notes: This table reports triple-difference (DDD) estimates of the interaction between beef bans and district-level beef consumption on children's test scores, separately for female (Panel A) and male (Panel B) children. Standard errors (in parentheses) are clustered at the state level. Reported p-values are obtained from wild cluster bootstrap. All models include controls for child age, household wealth, and survey year fixed effects.

mechanism—likely related to early-life nutritional deficits—affects both genders similarly.

3.5.2 Test Score Results by Age

Table 4 highlights meaningful heterogeneity in the effects of beef bans by age group. For children ages 5–12, exposure to beef bans in high–beef-consuming districts is associated with a 0.088 standard deviation reduction in composite test scores, with similarly sized declines in reading and math. These estimates are statistically significant for composite and reading outcomes and marginally significant for math. In contrast, the estimated effects for adolescents ages 13–16 are smaller (–0.048 for composite scores) and statistically insignificant across all outcomes. This divergence suggests that the cognitive consequences of beef bans are concentrated in middle childhood, a period when both nutritional inputs and school participation are especially critical for human capital accumulation. By adolescence, accumulated cognitive skills and potential dietary or educational adaptations may attenuate the immediate effects of such shocks.

We also obtain interacted regression coefficients to measure the treatment effects by age. Figures 7 and 8 show that the effect of the bans is largely concentrated among children ages 5-7, underscoring the role of nutrition in early childhood development.

Table 4: Triple-Difference Estimates: Effect of Beef Bans × Beef Consumers on Test Scores, by Age Group

	Composite Score	Reading Score	Math Score
Panel A: Children Ages 5–12			
Beef Ban × Beef Consumers	-0.088	-0.088	-0.088
	(0.039)	(0.037)	(0.043)
Observations	1,010,076	1,008,708	1,006,914
Bootstrap p-value	0.037	0.030	0.062
Panel B: Children Ages 13–16			
Beef Ban × Beef Consumers	-0.048	-0.024	-0.071
	(0.044)	(0.045)	(0.043)
Observations	412,094	411,600	410,959
Bootstrap p-value	0.194	0.440	0.197

Notes: This table reports triple-difference (DDD) estimates of the interaction between beef bans and district-level beef consumption on children's test scores, separately for two age groups: 5–12 (Panel A) and 13–16 (Panel B). Standard errors (in parentheses) are clustered at the state level. Reported p-values are obtained from wild cluster bootstrap. All models include controls for child gender, age, household wealth, and survey year fixed effects.

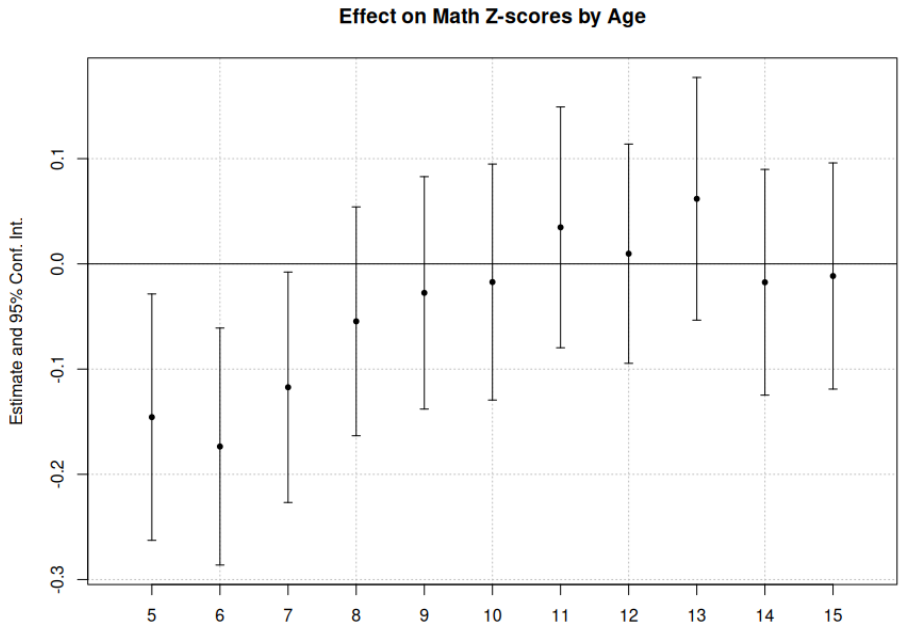


Figure 7: Triple-Difference Coefficient for Math Z-scores by Age

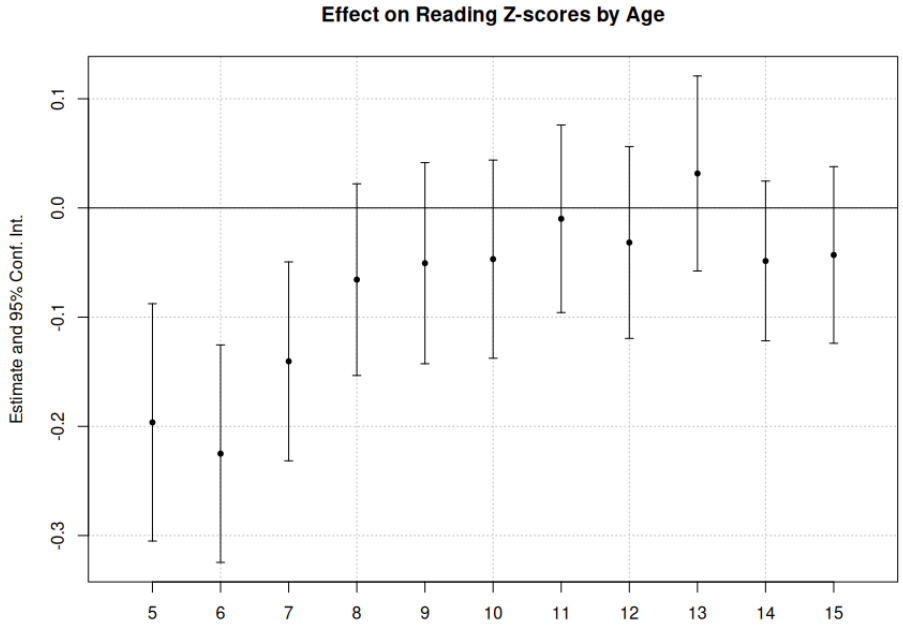


Figure 8: Triple-Difference Coefficient for Reading Z-scores by Age

3.6 Mechanisms – School Participation and Progression

Table 5: Interaction Effect of Beef Ban and Beef Consumption Prevalence

	Never Enrolled	Dropout	Enrolled	Dropout Index	On Track	Yrs Behind
Coef	0.003	0.006	−0.021	0.047	−0.031	0.061
p-value	0.324	0.090	0.079	0.080	0.119	0.213
N	1,648,478	1,648,478	1,648,478	1,648,478	1,648,478	1,426,854

Notes: Estimates from STATA's `reghdfe` with 9,999-replicate cluster bootstrap at the state level. The interaction term is either ban with dummy for belonging to above average beef consumer district. "Coef" is the interaction coefficient; "p-value" is the bootstrap p-value; "N" is the sample size. All effects are in SD units (or dummies) as appropriate.

Following our finding of adverse impacts of beef bans on learning outcomes, we examine their relationship with schooling participation and progression. We focus on six core indicators for each child: never-enrolled status, dropout status, current enrollment, a dropout index, on-track status (at least the expected grade for age), and years of grade delay ("years behind"). Consistent with Kling et al. (2007), Anderson (2008), and the safety-net evaluation framework of Hoynes et al. (2016), individual indicators are standardized to enable direct comparison in standard deviation units (or reported as dummies for binary variables).

The dropout index is defined as the mean of two binary indicators—(i) not currently enrolled and (ii) identified as a dropout—capturing both immediate non-participation and confirmed exit from schooling in a single metric.

Table 5 reports interaction estimates between the beef ban indicator and an indicator for residing in an above-average beef-consuming district, with p-values from 9,999-replicate state-clustered bootstraps. The point estimates suggest modestly worse schooling participation and progression in high-beef districts post-ban. Enrollment is lower by -0.021 ($p = 0.079$) and the dropout index higher by 0.047 ($p = 0.080$). On-track status falls by -0.031 ($p = 0.119$) and years behind rises by 0.061 ($p = 0.213$), though these are imprecisely estimated. Extensive-margin measures change little—never-enrolled is 0.003 ($p = 0.324$). With $N \approx 1.65$ million (slightly lower for "years behind"), the pattern is consistent with small, directionally adverse effects on school participation and progression in higher-beef districts after a ban, particularly among children already enrolled in school, rather than through extensive-margin shifts in ever or never having attended school.

3.7 Enrollment by Age

Table 6: Triple-Difference Estimates: Effect of Beef Bans × Beef Consumers on Schooling Outcomes, by Age Group

	Never Enrolled	Dropout	Enrolled
Panel A: Children Ages 5–12			
Beef Ban × Beef Consumers	0.004	0.003	-0.022
Bootstrap p-value	0.240	0.156	0.063
Observations	1,138,859	1,138,859	1,138,859
Panel B: Adolescents Ages 13–16			
Beef Ban × Beef Consumers	0.001	0.017	-0.022
Bootstrap p-value	0.650	0.046	0.059
Observations	509,619	509,619	509,619

Notes: This table reports triple-difference (DDD) estimates of the interaction between beef bans and district-level beef consumption on school participation outcomes, separately for children ages 5–12 (Panel A) and adolescents ages 13–16 (Panel B). Standard errors (not shown) are clustered at the state level. Reported p-values are obtained from wild cluster bootstrap. All models include controls for child gender, age, household wealth, and survey year fixed effects, with state-by-birth-year fixed effects absorbed.

Table 6 complements our earlier test score results by examining school participation outcomes across age groups. Consistent with the results for test scores, we find that children ages 5–12 in high–beef-consuming districts exposed to beef bans are less likely to be enrolled

(–2.2 pp, $p \approx 0.06$), with small and imprecise changes in never-enrollment and dropout. For adolescents ages 13–16, we also observe a decline in enrollment of similar magnitude (–2.2 pp) but, interestingly, a statistically significant increase in dropout (+1.7 pp, $p \approx 0.05$). These patterns suggest that while the immediate cognitive effects of beef bans are concentrated in younger children, consistent with our finding of substantial test score declines in the 5–12 cohort, exposure also appears to disrupt schooling trajectories for older adolescents, primarily through elevated dropout. This contrasts with our cognitive results for the 13–16 group, where test score effects were small and statistically insignificant, but aligns with evidence from Shah and Steinberg (2021) that policy shocks, such as NREGS, often disproportionately affect older children through altered schooling and work decisions. Taken together, these findings point to complementary pathways: early-life nutritional shocks may directly impair learning in primary-school-aged children while also pushing older adolescents out of school, reinforcing long-term human capital deficits through both cognitive and participation channels.

3.8 Dropout rates and test scores

Table 7: Dropout-Mediation by Age: Beef Ban × Beef Share on Test Scores

	Baseline DDD			**Mediated (Dropout)**		
Specification	All	< 13 yrs	≥ 13 yrs	All	< 13 yrs	≥ 13 yrs
Panel A: Math Scores						
Coef	–0.085	–0.088	–0.073	–0.079	–0.086	–0.056
Bootstrap p-value	(0.069)	(0.063)	(0.164)	(0.082)	(0.060)	(0.227)
N	1,363,103	960,039	403,064	1,363,103	960,039	403,064
Panel B: Reading Scores						
Coef	–0.071	–0.089	–0.026	–0.065	–0.085	–0.007
Bootstrap p-value	(0.042)	(0.029)	(0.410)	(0.054)	(0.029)	(0.811)
N	1,365,409	961,722	403,687	1,365,409	961,722	403,687

Table 7 presents our mediation analysis, testing whether increases in school dropout rates can account for the adverse triple-difference effects of beef bans on test scores. Panel A reports math results, Panel B reading.

In the full sample ("All"), the baseline Beef Ban × Beef Share interaction coefficient is –0.085 (p=0.069) for math and –0.071 (p=0.042) for reading, indicating modest declines in scores in high–beef-consuming districts under bans. When we add the child's dropout indicator as a mediator, the interaction effect attenuates to –0.079 (p=0.082) in math and –0.065 (p=0.054) in reading, suggesting that roughly 10–15 percent of the original test-score penalty operates through increased dropout.

Splitting by age reveals that the mediation channel is strongest among younger children. For those under 13, baseline effects are: 0.088 (p=0.063) in math and -0.089 (p=0.029) in reading; controlling for dropout reduces these to -0.086 (p=0.060) and -0.085 (p=0.029), respectively. Among older children ($\geqslant$ 13 yrs), the baseline effects are smaller (–0.073 , p=0.164 in math; –0.026 , p=0.410 in reading) and largely unchanged when dropout is included (–0.056 , p=0.227; –0.007 , p=0.811).

These patterns show that elevated dropout in the wake of beef bans helps explain a nontrivial share of score declines, especially for younger cohorts, consistent with school enrollment as a key mechanism linking dietary restrictions to cognitive outcomes.

3.8.1 Casual mediation analysis

Causal Mediation Framework. We also explore mechanisms in a potential outcomes and counterfactual analysis framework using causal mediation analysis. This involves estimating:

$$M_i = \alpha_0 + \alpha_1 \texttt{interact}_i + \mathbf{X}_i'\boldsymbol{\alpha} + \mu_{s(i)t(i)} + \epsilon_i^M \tag{1}$$

$$Y_i = \beta_0 + \beta_1 \texttt{interact}_i + \beta_2 M_i + \mathbf{X}_i'\boldsymbol{\beta} + \mu_{s(i)t(i)} + \epsilon_i^Y \tag{2}$$

where M_i is the dropout index taking three discrete values, and Y_i is the test score. The controls $\mathbf{X}_i$ and fixed effects $\mu_{s(i)t(i)}$ are identical to those used in the main regressions, ensuring comparability. In our analysis, as in baseline results, the treatment variable `interact` is defined as the interaction between a state-level beef ban (`eitherban`) and whether the child lives in a district with above-average prevalence of beef-consuming communities. This variable captures the intensity of exposure to identity-based dietary restrictions that disproportionately affect communities culturally or religiously associated with beef consumption. It allows us to estimate the heterogeneous cognitive impact of these bans on children in affected districts.

The mediation model decomposes the treatment effect into:

- **Natural Direct Effect (NDE)**: The effect of treatment not operating through the mediator.
- **Natural Indirect Effect (NIE)**: The effect mediated through changes in the dropout index, computed as $\alpha_1 \times \beta_2$.

- **Controlled Direct Effect (CDE)**: The effect of treatment holding the mediator fixed at a specific value ($M = -0.290$).
- **Marginal Total Effect (MTE)**: The sum of NDE and NIE.

The MTE from `paramed` and the treament effects form our baseline model from the regression differ because they are identified through different frameworks. The regression model estimates a single conditional association and does not decompose mechanisms or account for post-treatment confounding or potential endogeneity of the mediator. In contrast, the mediation framework models both mediator and outcome equations separately and applies counterfactual logic to estimate how the mediator channels part of the treatment effect. This often results in slightly larger MTEs, as the indirect pathway is not "controlled away" as it may be implicitly done in a single regression.

Results and Interpretation. Empirically, we find that the MTEs reported in Table 8 are slightly larger than the corresponding regression estimates: -0.102 for math, and -0.089 or reading. The NIE accounts for approximately 14% and 19% of the respective MTEs, with the remainder attributable to direct effects. This dominance of the direct pathway suggests that the negative cognitive consequences of beef bans are not driven solely by reduced school engagement.

Table 8: Estimates of Mediation Effects on Test Scores

Effect	**Subject**	**Estimate**	**SE**
Controlled Direct Effect (CDE)	Math	-0.084	0.0031
	Reading	-0.063	0.0031
Natural Direct Effect (NDE)	Math	-0.088	0.0030
	Reading	-0.072	0.0030
Natural Indirect Effect (NIE)	Math	-0.014	0.0006
	Reading	-0.017	0.0007
Marginal Total Effect (MTE)	Math	-0.102	0.0030
	Reading	-0.089	0.0031

Notes: All coefficients (point estimates and standard errors) are from causal mediation analysis using the `paramed` command in Stata. Mediator is a composite measure of two indicators in our data that get at dropout: a question on whether a kid is out of school due to dropout and a measure based on missing data in school, grades/class on whether a child is not currently enrolled or not.

These mediation results align with the recent findings from Behrman et al. (2014), who emphasize that schooling alone is not the sole or even dominant determinant of cognitive

test outcomes. Using data from Guatemala, they demonstrate that adult cognitive skills are significantly shaped by early-life nutrition (measured by height-for-age at age 6) and post-school skilled work experiences, alongside schooling itself. Their evidence strongly suggests that multiple, complementary channels beyond enrollment or formal schooling significantly contribute to cognitive achievement. Similarly, Miguel and Kremer (2004) studied school-based deworming in Kenya and documented substantial gains in school attendance (about 25%) but found no immediate improvements in test scores, underscoring that attendance alone does not guarantee enhanced cognition.

Consistent with these findings, our analysis also indicates that while dropout is a meaningful mediator of the treatment effect, the substantially larger direct effects highlight the critical importance of alternative pathways such as nutrition, early-life health, and social identity–linked stressors. These mechanisms may be triggered by cultural stigma, dietary changes, or broader household resource reallocations following restrictive state policies.

3.9 Supplemental investment in education

Some families may choose to supplement their child's schooling with additional tutoring. We are able to observe both the prevalence of extracurricular tutoring, colloquially referred to as "tuition classes" in India, as well as the amount paid in the form of tutoring fees. 22% of children in the sample receive extracurricular tutoring. Investment in tutoring for a child may be complementary to other educational investments, or it may be a substitute for them. Table 9 presents triple-difference estimates of the effect of beef sale/possession ban $\times$ beef-share interaction on both the probability of paying for tutoring, and the fee amount among those who do pay. Column (1) shows an estimated coefficient of –0.00004 (wild-cluster bootstrap p = 0.999) on the interaction term for the binary tuition indicator, based on a sample of 1.51 million observations—effectively zero and precisely estimated. Column (2) reports a point estimate of –9.8 rupees (p = 0.390) on the interaction for the continuous tuition amount, drawn from 241 thousand fee-paying children, again statistically indistinguishable from zero. In other words, we find no evidence that beef bans systematically alter either households' decision to pay for tutoring, or the magnitude of fees. This null pattern suggests that the changes in schooling participation documented earlier do not reflect compensatory shifts in out-of-pocket educational expenditures.

Table 9: DDD Estimates: Beef Ban × Beef Share Interaction on Tutoring Outcomes

	Tutoring (Yes/No)	**Fee Amount**
Coef	−0.00004	−9.808
p-value	(0.999)	(0.390)
N	1,507,702	241,282

3.10 Reading at grade level

Table 10 reports the estimated impact of beef bans on grade-appropriate reading outcomes for children in classes 1 and 2, as well as for a combined indicator that captures whether children in these grades can read at the level expected for their grade. The interaction term between beef ban exposure and the district-level share of traditional beef-consuming groups is negative across all specifications, though the magnitudes are small and not statistically significant at conventional levels. It is important to note that only 8.7% of 6-year-olds and 21% of 7-year-olds in the data read at a first grade level or higher, and only 20% of 8-year-olds in the data read at a second grade level or higher.

Table 10: Impact of Beef Bans on Grade-Appropriate Reading

	Class 1 Read OK	Class 2 Read OK	Grade-Appropriate Read
Interaction Coef	-0.00165	-0.00270	-0.00145
Bootstrapped p-value	0.360	0.515	0.301
Observations	1,648,478	1,648,478	357,943

Specifically, the estimated coefficients range from –0.001 to –0.003, with bootstrapped p-values between 0.30 and 0.52, indicating no meaningful evidence of a decline in reading outcomes associated with beef ban exposure in these early primary grades. While the direction of the effects is consistent with the hypothesis that beef bans could reduce access to affordable dietary sources of iron and thereby impair cognitive development, the lack of statistical significance suggests that any such effects on reading proficiency in the early years of schooling are either minimal or require a larger sample or longer exposure window to detect. It is also possible that because so few children read at grade level, the impacts we observe are at lower levels of proficiency. This divergence may reflect differences in how nutritional shocks affect basic reading ability in early grades compared to more complex cognitive tasks or cumulative educational outcomes.

3.11 Continuous Measure of Beef Consumer Proportion

A limitation of using the indicator for high beef consumer in our regression, is that in Gujarat, there are no districts with a proportion of beef consumers greater than the national mean. As a robustness check, instead of using an indicator variable, we use the proportion of beef consumers in a district as the measure of exposure. By using a continuous measure of beef consumer share and pooling across all states, this approach maximizes within-state variation and ensures that the estimated interaction captures a broader range of exposure differences across the sample.

Table 11 presents the estimated effects of the interaction between the beef ban indicator and the continuous measure of district-level beef consumer share on standardized reading and math scores. The estimates now represent impact of beef sale/possession bans moving from a district with 0 to 100% share of beef consumers.

Table 11: Effect of Beef Ban × Beef Consumer Share on Test Scores

	Reading	**Math**
Panel A: Overall Sample		
Coefficient	-0.506	-0.449
p-value	0.065	0.256
N	1,420,308	1,417,873
Panel B: Ages 5–7		
Coefficient	-0.459	-0.361
p-value	0.053	0.152
N	347,872	347,149
Panel C: Ages 5–12		
Coefficient	-0.512	-0.436
p-value	0.072	0.254
N	1,008,708	1,006,914
Panel D: Ages 13–16		
Coefficient	-0.491	-0.484
p-value	0.059	0.272
N	411,600	410,959

Notes: Table reports coefficient estimates for the interaction term `Beef Ban` × `Beef Consumer Share` from regressions of standardized test scores on the interaction, controls, and fixed effects. p-values are from wild cluster bootstrap (9,999 reps) clustered at the state level.

Across all specifications, the interaction term is negative, indicating that districts with higher baseline beef consumption experience larger declines in test scores following the im-

plementation of beef bans. In the full sample (Panel A), the estimated coefficients are −0.51 for reading and −0.45 for math, with the reading effect marginally significant at conventional levels (wild cluster bootstrap $p = 0.065$).

The age-disaggregated results (Panels B – D) suggest that the magnitude of the reading effect is broadly similar across age groups, ranging from −0.46 to −0.51, with p-values between 0.053 and 0.072. The math effects are somewhat smaller in magnitude (−0.36 to −0.48) and less precisely estimated, with bootstrap p-values between 0.152 and 0.272. The pattern is consistent with the hypothesis that children in high-beef-consuming districts suffer academic losses after bans, with reading scores showing more robust declines than math scores.

Overall, the results highlight a persistent negative association between beef bans and cognitive outcomes in communities more reliant on beef consumption, particularly for reading achievement. The effects remain stable across narrow and broad age cohorts, suggesting that the observed impacts are not driven solely by a particular stage of schooling.

4 Discussion and Conclusion

Our results paint a consistent picture of the developmental costs of beef bans. This study contributes to the literature on fetal origins, nutrition, and identity politics. Children exposed to bans in high beef-consuming districts exhibit stark deficits in cognitive performance: 0.07–0.09 standard deviations lower test scores in composite, reading, and math—driven primarily by those ages 5–12, a critical stage for skill formation. These effects are similar across boys and girls, indicating that the underlying mechanism, likely reduced access to affordable, iron-rich foods, affects children broadly. Schooling outcomes mirror this pattern: enrollment declines are evident for younger children, while adolescents experience a significant rise in dropout, echoing prior evidence that policy shocks can disrupt schooling decisions for older cohorts. Notably, these participation changes are not offset by shifts in parental investment as measured by in spending on private tutors, nor do we find detectable impacts on early grade-level reading. Taken together, these findings highlight that policies rooted in cultural and moral regulation that impact nutrition can impose hidden costs on children's human capital accumulation.

Our results show that bans on the sale and possession of beef can reduce test scores and raise the risk of school dropout among beef-consuming communities, who are primarily affected by these bans. These changes occur in the context of severe existing educational deficits, as shown in Figure 2. The evidence suggests that these effects may operate through

nutritional pathways, particularly maternal anemia and iron deficiency during pregnancy and early childhood. Deficits in maternal nutrition can contribute to lasting cognitive delays in children, particularly at critical ages for skill formation.

The schooling consequences we document: lower enrollment among young children, and higher dropout among adolescents, underscore how early nutritional shocks cascade into later educational outcomes. These patterns are consistent with the broader fetal origins and early childhood development literature, which emphasizes that small disruptions in early life health can have enduring impacts on human capital. As a policy recommendation, improvements in the nutritional content of school lunches can accomplish meaningful improvements in test scores at a relatively low cost. India has a universal school lunch program known as the Mid-Day Meal program; however, concerns remain about the level of macro- and micro-nutrients in the meals (Ramachandran, 2019). Policy interventions focused on improving the nutritional content of school meals have been shown to improve children's test scores in the US, and could potentially be successful in India as well (Anderson et al., 2018).

By highlighting the hidden costs of beef sale and possession bans, our findings contribute to the understanding that policies rooted in cultural and moral regulation can inadvertently exacerbate developmental inequality. As governments weigh such regulations, it is essential to recognize that restrictions on affordable, nutrient-rich foods may impose long-run human capital costs that are borne disproportionately by children in affected communities.

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