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Associations Between the Transition to Cleaner Cooking Energy Use and Child Health Outcomes in India

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Abstract

India's Pradhan Mantri Ujjwala Yojana (PMUY), launched in 2016, provides below-poverty-line (BPL) households with free liquefied petroleum gas (LPG) connections. During the same period, national and state governments implemented multiple additional programs targeting BPL households, yet the health implications of these policies remain understudied. We used data from India's National Family Health Surveys (NFHS-4, 2015-2016; NFHS-5, 2019-2021) to examine area-level associations between changes in non-clean fuel use (solid fuels and kerosene), reflecting shifts associated with clean energy policies, and child health outcomes nationwide. We applied a precision-weighted approach that incorporates survey design and sampling variability to estimate district-level prevalence of child health outcomes and socioeconomic indicators across survey periods. In parallel, we implemented a difference-in-differences (DiD) design with a non-equivalent comparison group to compare outcomes among BPL households that reported LPG as their primary cooking fuel with those that did not. A 10-percentage-point higher prevalence of non-clean fuel use was associated with a 0.70 percentage-point higher prevalence of stunting (95% CI: 0.22, 1.18), while estimates for other outcomes were generally small and imprecise. DiD estimates were similarly centered near the null across all child health outcomes. Because NFHS-5 was conducted during the COVID-19 pandemic, a period marked by disruptions to health services, household economic conditions, and energy use patterns, these factors may have attenuated observed associations. This analytic framework can be applied to future NFHS rounds to assess whether longer-term or post-pandemic trends reveal clearer relationships between clean energy transitions and child health.

1 Introduction

The incomplete combustion of non-clean (polluting) cooking fuels, including solid fuels and liquid kerosene, releases pollutants such as particulate matter (PM), black carbon (BC), and carbon monoxide (CO), among others, that adversely affect health. Women and young children experience the highest exposure to household air pollution (HAP) because of prolonged time spent in cooking environments. Extensive epidemiologic evidence links HAP to neonatal and infant mortality (Epstein et al., 2013; Patel et al., 2015), and to several major preventable causes of morbidity and mortality in children, including low birth weight (<2500 g), impaired linear growth as measured by stunting, and acute respiratory infection (ARI) (Bennitt et al., 2021; Lee et al., 2020a).

Low birth weight is a critical public health indicator because it strongly predicts survival, growth, and long-term health (Kramer, 1987). Stunting is a widely-used marker of chronic undernutrition and early-life deprivation (deSouza et al., 2022b), associated with impaired physical growth, weakened immune function, and delayed cognitive development (Victora et al., 2008). Because stunting reflects cumulative exposures during the first 1,000 days of life, a critical developmental window, understanding its determinants is central to improving population health (Black et al., 2013; UNICEF and others, 2013; Victora et al., 2008). ARIs remain a leading cause of death among children under five years of age worldwide (Liu et al., 2015; Organization, 2023). Together, low birth weight, stunting, and ARI represent sensitive and well-established indicators of how household environmental conditions, particularly air quality, are associated with child health (de Onis and Branca, 2016; Schwartz, 2004; Stein et al., 2006; Zar et al., 2024).

1.1 Mechanisms Linking Exposure to HAP and Child Health

HAP is associated with neonatal and infant mortality through multiple, overlapping biological pathways operating during pregnancy, delivery, and the early postnatal period (Smith et al., 2014). Prenatal exposure to fine particulate matter ($PM_{2.5}$) and combustion byproducts can impair placental function, restrict fetal growth, and increase the likelihood of preterm birth, all strong predictors of neonatal death (Silbergeld and Patrick, 2005; Šrám et al., 2005). After birth, exposure to polluted air increases vulnerability to hypoxia, respiratory infection, and impaired thermoregulation, while toxic pollutants may compromise immune function, reduce lung capacity, and exacerbate complications related to prematurity (Proietti et al., 2013).

Air pollution is also associated with low birth weight through oxidative stress and systemic inflammation, which can reduce uteroplacental blood flow and impair fetal oxygen and nutrient supply (Fussell et al., 2024; Li et al., 2025). Carbon monoxide reduces maternal oxygen-carrying capacity, while polycyclic aromatic hydrocarbons, metals, and ultrafine particles may accumulate in placental tissue and interfere with trophoblast development and nutrient transport (Kannan et al., 2007; Longo, 1977). Chronic exposure is also associated with maternal conditions such as hypertensive disorders, anaemia, and respiratory infections, which are linked to intrauterine growth restriction (Villar et al., 2006).

The mechanisms linking HAP and childhood stunting are less well characterized (Sinharoy et al., 2020), although several plausible mechanisms have been proposed (deSouza et al., 2022b). Chronic exposure may induce systemic inflammation that diverts energy away from linear growth and disrupts endocrine regulation (Xu et al., 2022). Pollution-related respiratory and enteric infections can increase metabolic demands and reduce nutrient absorption, while damage to the intestinal barrier may contribute to environmental enteric dysfunction. Prenatal growth restriction may also place children on persistently lower postnatal growth trajectories (Sinharoy et al., 2020).

Air pollution is associated with increased risk of ARI through impairment of mucociliary clearance, inflammation of the airway epithelium, and suppression of immune responses. Pollution may increase airway permeability, facilitating pathogen entry and replication, while repeated exposure can alter lung development, increasing susceptibility to infection and disease severity in early childhood (Esposito et al., 2014; Gilliland et al., 1999).

1.2 Existing Evidence of Associations between HAP and Child Health

Hundreds of observational studies, natural experiments, and quasi-experimental evaluations have documented strong associations between household air pollution and adverse maternal and child health outcomes (Gould et al., 2025; Lee et al., 2020b). However, recent randomized and quasi-experimental evaluations of clean cooking interventions, including in India, have reported health estimates that are often modest in magnitude and imprecisely estimated (Checkley et al., 2024; Clasen et al., 2022; Raheel et al., 2025; Younger et al., 2024).

Several factors may explain these patterns. First, exposure reductions achieved by clean fuel interventions may be insufficient to produce measurable health gains. Here, 'insufficient' refers to both the magnitude and persistence of exposure reduction: although LPG interventions reduce HAP, post-intervention $PM_{2.5}$ concentrations often remain well above WHO guideline levels due to continued use of polluting fuels (fuel stacking) and incomplete displacement of biomass. As a result, the contrast in exposure between intervention and comparison groups may be limited, constraining the ability to detect differences in outcomes such as stunting or birth weight over typical study periods.

Second, interventions may be implemented after critical prenatal exposure windows have passed, limiting relevance for outcomes determined early in life. Third, follow-up periods are often too short to capture longer-term developmental processes, particularly for outcomes such as linear growth. Fourth, heterogeneity in stove performance, ventilation, and kitchen characteristics may attenuate realized exposure reductions even among adopting households. Finally, competing determinants of child health, including maternal undernutrition, infection burden, and broader socioeconomic constraints, may outweigh or obscure associations with reductions in household air pollution.

These considerations suggest that intervention-based evidence may not fully capture the health implications of broader, population-level changes in household energy use. Gradual but widespread shifts in fuel use, such as those driven by policy or infrastructure expansion, may produce larger or more sustained exposure changes than those observed in short-term trials. Evaluating such transitions requires study designs that leverage spatial and temporal variation in exposure at scale.

1.3 India's Clean Energy Policies

India has experienced substantial declines in population exposure to HAP over the past decade, with the proportion exposed falling from 63% in 2013 to 42% in 2023 (State of Global Air, 2023). Nevertheless, an estimated 938,000 deaths in 2023 remained attributable to HAP, with a disproportionate burden among children under five years of age (State of Global Air, 2023).

To address this burden, India implemented two major national initiatives: universal electrification under the Saubhagya scheme (2017) and large-scale expansion of clean cooking access through the Pradhan Mantri Ujjwala Yojana (PMUY), launched in 2016. Saubhagya electrified approximately 214 million homes, while PMUY provided about 90 million households with subsidized LPG connections (deSouza et al., 2025). Under PMUY, women from below-poverty-line (BPL) households received a one-time subsidy of Rs 1600 (~22 USD) to cover LPG connection and setup costs.

These policies coincided with multiple concurrent welfare programs targeting housing, electrification, and health (e.g., Pradhan Mantri Awas Yojana, Ayushman Bharat), complicating efforts to isolate the contribution of any single program. Nonetheless, available evidence indicates that PMUY and related initiatives were associated with substantial increases in reported LPG access, with national clean cooking prevalence rising from 36% in 2015-16 to 50% in 2019-21 (Majumdar et al., 2023). Quasi-experimental analyses estimate an approximately 8 percentage-point higher probability of LPG connection among BPL household (Gill-Wiehl et al., 2022), while national analyses report higher odds of reporting clean fuel use (odds ratio = 1.86) (Majumdar et al., 2023).

However, increased access has not consistently translated into sustained displacement of traditional fuels. Fuel stacking remains common: PMUY has been associated with modest increases in LPG consumption (approximately 0.7 kg per household per year) without clear increases in refill frequency or exclusive use (Gill-Wiehl et al. 2022). Field studies report that 60-80% of LPG adopters continue to use biomass, driven by affordability constraints, cooking practices, and supply reliability (Gould and Urpelainen, 2018; Kar et al., 2019). Thus, while PMUY substantially expanded access, corresponding changes in exposure may be more limited.

Although adoption and access have been extensively studied, empirical evidence linking policy-driven fuel transitions to realized exposure reductions and child health remains limited. To address this gap, we use repeated National Family Health Survey (NFHS) data to examine how district-level changes in the prevalence of non-clean fuel (non-CF) use are associated with trends in infant and neonatal mortality, low birth weight, stunting, and ARI. Building on prior NFHS-based work (deSouza et al., 2025), we combine precision-weighted district-level analyses with individual-level difference-in-differences designs to characterize both population-level associations and policy-relevant contrasts among BPL households.

2 Methods and Materials

2.1 NFHS Data

We used data from the fourth (NFHS-4; January 2015-November 2016) and fifth (NFHS-5; June 2019-April 2021) rounds of India's National Family Health Survey. NFHS surveys are nationally representative, repeated cross-sectional household surveys that collect detailed information on socioeconomic status, demographics, health, and nutrition, with a particular emphasis on maternal and child health. Because households and individuals are not followed longitudinally, each survey round constitutes an independent cross-section of the national population.

NFHS employs a stratified two-stage cluster design. Primary sampling units (PSUs), villages in rural areas and census enumeration blocks in urban areas, were selected within each district (640 districts in NFHS-4; 707 in NFHS-5). In the second stage, 25-30 households were selected within each cluster using equal-probability systematic sampling. All usual residents were enumerated, after which women aged 15-49 years and men aged 15-54 years completed standardized questionnaires administered by trained field staff.

2.1.1 Child health outcomes

We examined five child health outcomes: neonatal mortality, infant mortality, low birth weight, stunting, and acute respiratory infection (ARI).

Mortality outcomes were derived from complete birth histories reported by mothers, including month and year of birth and, where applicable, death. Neonatal mortality was defined as death within the first month of life, and infant mortality as death within the first year.

Low birth weight was defined as <2,500 g. Birth weight was obtained from health cards when available or maternal recall otherwise. Because recall-based reporting may introduce measurement error, particularly for older children, this outcome may be subject to non-differential misclassification.

Stunting was defined as height-for-age z-score < −2 standard deviations using the WHO Child Growth Standards. Anthropometric measurements were collected by trained enumerators using standardized equipment and protocols, and are generally considered high-quality, although random measurement error may attenuate estimated associations.

ARI was defined based on maternal report of symptoms consistent with ARI (cough accompanied by rapid or difficult chest-related breathing) in the two weeks preceding the survey. This measure captures symptom-based illness rather than clinically confirmed diagnoses and is therefore susceptible to reporting error.

Analyses included children under five residing in clusters with valid geographic coordinates, excluding visitors and retaining only children born in the interviewed household (**Table S1**).

Because NFHS surveys are repeated cross-sectional surveys, within-household changes in fuel use and subsequent health outcomes cannot be observed. Accordingly, policy analyses rely on between-period comparisons using district-level first differences and individual-level difference-in-differences designs.

For mortality analyses, we restricted samples to ensure outcome observability: births ≥12 months before interview for infant mortality and ≥1 month before interview for neonatal mortality. To align with PMUY eligibility, analyses of clean fuel adoption were restricted to households reporting LPG as the primary cooking fuel, excluding biogas and electricity (**Table S2**).

2.1.2 Exposure definition: clean versus non-clean cooking fuels

Households were classified as using clean fuels if the primary cooking fuel was electricity, LPG, or natural gas/biogas, and non-clean fuels if the primary fuel was coal, charcoal, wood, kerosene, straw/shrubs/grass, agricultural residue, or dung. We use the term non-clean fuel (non-CF) to denote these polluting fuels; throughout, results are presented in terms of higher prevalence of non-CF use, which corresponds inversely to clean fuel adoption. Given the focus of PMUY, we additionally examined LPG use specifically.

Cooking fuel use was self-reported based on the household's primary fuel. This measure does not capture secondary fuel use (fuel stacking), which is common and may lead to exposure misclassification. As a result, households classified as using clean fuels may continue to experience substantial exposure to household air pollution.

NFHS also records dwelling characteristics, including whether the household has a separate kitchen. In supplementary analyses, we examined households using non-clean fuels without a separate kitchen as a higher-exposure subgroup, consistent with prior work (Sidhu et al., 2017).

2.1.3 Covariates

District-level models adjusted for changes in the prevalence of key socioeconomic and demographic characteristics, including the proportion of households in the poorest wealth quintile, households headed by individuals with no formal education, household smoking, maternal underweight, early marriage, improved sanitation, and electricity access. We also adjusted for changes in population composition, including the proportion of Scheduled Castes, Scheduled Tribes, Other Backward Classes, and Muslims, derived from NFHS data.

Models included region fixed effects (North, Central, East, West, South, and North-East; **section S1**). In addition, we adjusted for district-level environmental change metrics, including ambient $PM_{2.5}$, the Palmer Drought Severity Index, the Enhanced Vegetation Index, and a heat stress index (**section S2**).

Individual-level models adjusted for child sex, birth order, and singleton status; maternal education, age category, height, and underweight status (BMI <18.5 kg/m²); and household urban/rural residence, improved sanitation, electricity, safe drinking water, and poorest wealth quintile. For stunting and ARI, we additionally included linear and quadratic terms for child age (months).

Environmental exposures ($PM_{2.5}$, PDSI, EVI, heat stress) were assigned at the cluster level using displaced NFHS GPS coordinates and averaged within 2 km (urban) or 5 km (rural) buffers (deSouza et al., 2023, 2022a). Models included district fixed effects and state-by-month fixed effects to adjust for spatial and seasonal confounding.

2.2 Statistical Models

2.2.1 District-level prevalence estimation

We estimated precision-weighted district-level prevalences of different NFHS variables using four-level multilevel logistic regression models. Because district boundaries differed between NFHS-4 and NFHS-5, all estimates were harmonized to the 722 districts defined in NFHS-5. NFHS-4 clusters were assigned to NFHS-5 districts based on cluster centroids (Rajpal et al., 2025).

The hierarchical structure comprises individuals (or households) at level 1 (i), clusters at level 2 (j), districts at level 3 (k), and states at level 4 (l). The model is specified as:

$$logit(NFHS\ variable_{ijkl}) = \alpha_0 + u_{0jkl} + v_{0kl} + f_{0l} \quad (1)$$

$NFHS\ variable_{ijkl}$ represents the binary outcome or covariate of interest from the NFHS survey. Where α_0 is the constant, and represents the median log odds of each covariate across all of India; u_{0jkl}, v_{0kl}, and f_{0l} are the residuals at the cluster, district, and state levels, respectively. The residuals are assumed to be normally distributed with a mean of 0 and a variance of σ^2_{u0}, σ^2_{v0}, and σ^2_{f0}, respectively. These variance terms can be interpreted as within-district between-cluster variation (σ^2_{u0}), within-state between-district variation (σ^2_{v0}), and between-state variation (σ^2_{f0}).

District-specific predicted probabilities were obtained by transforming the estimated district- and state-level linear predictors: $exp\ (\alpha_0 + v_{0kl} + f_{0l})\ /(1 + exp\ (\alpha_0 + v_{0kl} + f_{0l})\ )$. Unlike Rajpal et al., (2025), who first estimated cluster-level prevalences and then aggregated to districts, we directly estimated district-level prevalences from the multilevel model

Models were fitted using the lme4 package in R. District-level estimates were obtained for two periods: 2015-2016 and 2019-2021. Pairwise correlations among modeled district-level variables were small (**Figure S1**).

2.2.2 District-level regression models

We estimated associations between changes in district-level non-clean fuel use and changes in child health outcomes using linear regression models of the form:

$$\Delta_{Outcome_{district}} = \beta_0 + \beta_1 \times \Delta NonCF\ use_{district} + \sum_{covariates} \beta_{covariate} \times \Delta covariates_{district} + \varepsilon_{district} \quad (2)$$

where $\Delta Outcome_{district}$ denotes the change in the prevalence of a given child health outcome in district d, $\Delta NonCF_{district}$ is the change in the prevalence of non-clean fuel use. $Covariates_{district}$ represent a vector of district-level covariates, and $\varepsilon_{district}$ is the error term. The coefficient β_1 represents the association of interest between changes in non-clean fuel use and changes in the health outcome.

Because districts within the same state may share unobserved characteristics, standard errors were clustered at the state level. Results are reported as percentage-point differences in each health outcome associated with a 10-percentage-point difference in non-clean fuel use.

We assessed robustness using alternative covariate sets and population-weighted models (WorldPop weights for children <1 and <5 years). To examine heterogeneity, we interacted $\Delta NonCF_{district}$ with regional indicators and estimated region-specific associations, recognizing that fuel adoption and health effects may vary across socioeconomic and institutional contexts. We also estimated cross-sectional models separately for NFHS-4 and NFHS-5 to examine time-specific associations between non-clean fuel prevalence and child health outcomes.

Finally, we re-estimated the fully adjusted models using outcome prevalences restricted to BPL households, the primary target population of PMUY, and separately, non-BPL households to assess whether associations between $\Delta NonCF_{district}$ and $\Delta Outcome_{district}$ differed by policy eligibility.

2.2.3 Difference-in-Difference (DiD) analyses using individual-level data

We estimated associations between cooking fuel type and child health outcomes using multivariable logistic regression models within a difference-in-differences (DiD) framework. The analysis compares differences in outcomes between NFHS-4 (pre-PMUY) and NFHS-5 (post-PMUY) among children in below-poverty-line (BPL) households that reported LPG as their primary cooking fuel versus those that reported polluting cooking fuels. Because the NFHS surveys are repeated cross-sections, this design estimates differences in associations across policy periods rather than within-household causal effects. The DiD model was specified as:

$$log(\frac{p_{it}}{1-p_{it}}) = \beta_0 + \beta_1 TRT_{it} + \beta_2 AFT_t + \beta_3 TRT_{it} \times AFT_t + \beta_4 X_{it} + \gamma_{sm} + \alpha_d + \epsilon_{it} \quad (3)$$

Where $p_{it} = P(y_{it} = 1|.)$, denotes that the probability that child i at time t experiences the outcome y_{it}. Outcomes were modeled separately as binary indicators for neonatal mortality, infant mortality, under-five mortality, low birth weight, stunting, and ARI. TRT_{it} is an indicator equal to 1 if the household reported LPG as its primary cooking fuel and 0 if it used a polluting fuel. AFT_t is an indicator for the post-PMUY period (NFHS-5). The interaction term $TRT_{it} \times AFT_t$ yields the DiD estimator, β_3, representing the differential change in the log-odds of the outcome for children in LPG-using BPL households relative to children in non-LPG BPL households between the two survey waves.

X_{it} includes child, maternal, household, and environmental covariates described in Section 2.1.3.2. We included district fixed effects, α_d, to control for time-invariant location-specific unobserved confounding and state-by-month-of-birth fixed effects, γ_{sm}, to capture seasonal and state-level time varying factors. ϵ_{it} the error term. Standard errors were clustered at the state level to account for within-state correlation.

The DiD framework relies on a parallel trends assumption, that outcomes among comparison groups would have evolved similarly in the absence of changes in cooking fuel use. Because data prior to NFHS-4 were unavailable, this assumption could not be formally tested and may be violated if households reporting LPG use differ systematically. Accordingly, results from these models should be interpreted as associational contrasts rather than causal effects.

To strengthen robustness to potential violations of this assumption, we implemented a propensity-score-weighted (PSW) DiD estimator that combines inverse-probability weighting with fixed-effects outcome regression (Sant'Anna and Zhao, 2020). We first estimated household-level propensity scores for LPG use using pre-intervention covariates capturing demographic characteristics, maternal factors, birth history, environmental exposures, and household amenities. These scores were used to construct inverse-probability weights targeting the average treatment effect on the treated (ATT). Covariate balance was assessed using standardized mean differences, with all post-weighting absolute differences <0.01, indicating strong balance between comparison groups. We then estimated weighted logistic DiD models including the same covariates and fixed effects, with the interaction between LPG use and survey period yielding the DiD contrast.

All statistical analyses were performed using R 4.5.0. Results are presented as point estimates with 95% confidence intervals; p-values are reported for completeness but are not used as the primary basis for inference.

3 Results

3.1 Descriptive Statistics

Descriptive statistics for district-level prevalence of child health outcomes, cooking fuel use, and covariates in 2016 (NFHS-4) and 2021 (NFHS-5) are presented in **Table 1**.

The prevalence of neonatal mortality, infant mortality, and under-five mortality was lower in NFHS-5 compared with NFHS-4, declining from 2.6% to 2.2%, 3.7% to 3.1%, and 4.1% to 3.4%, respectively (**Table 1**; **Figure S2**). Mortality remained highest in districts in Central and North-East India, while larger absolute reductions were observed in West and South India (**Figure 1**).

The prevalence of low birth weight, stunting, and ARI was also lower in NFHS-5 than in NFHS-4, from 17.2% to 16.2%, 35.6% to 33.2%, and 2.5% to 2.0%, respectively (**Table 1**; **Figure 1**). Low birth weight was more prevalent in the North and West, stunting in Central and West India, while ARI showed no strong regional clustering (**Figure S3**).

Household reliance on non-clean fuels (non-CF; solid fuels or kerosene) was highest in poorer districts in Central and North-East India (**Figure S4**). The mean district-level prevalence of non-CF use was lower in NFHS-5 than NFHS-4 (66.2% vs. 47.8%), as was the prevalence of households using non-CF without a separate kitchen (26.4% vs. 13.8%) (**Table 1**). These patterns indicate a widespread transition toward cleaner cooking fuels across districts (**Figure 1F**).

Correspondingly, the prevalence of LPG use was higher in NFHS-5 (53.0%) compared with NFHS-4 (33.4%). Spatial patterns of LPG uptake closely mirrored reductions in non-CF use (**Figure S4**).

Changes in key covariates are shown in **Figure 2**. Distributions were generally stable over time, although improvements were observed in sanitation and electricity access. Districts in Central and East India continued to exhibit higher levels of poverty and lower educational attainment, alongside lower prevalence of non-smoking households and improved sanitation, despite relatively high access to safe drinking water (**Figures S5-S9**).

Environmental exposures showed modest changes over time (**Figures S10-S11**). Spatial patterns of LPG use among BPL households were similar to those observed in the full sample (**Figure S12**).

***Table 1**: Descriptive statistics of the prevalence (unit: %) of the health outcomes, neonatal mortality, infant mortality, child mortality, low birth weight, and stunting, exposures, and covariates at the district level using data from the NFHS-4 and NFHS-5 surveys. The number of observations used to estimate prevalences of different variables are provided in **Table S1**. Mean (standard deviation) is reported.*

	NFHS-4 (%)	NFHS-5 (%)	Change in Prevalence between NFHS-5 and NFHS-4
Outcome			
Neonatal mortality	2.6% (1.0%)	2.2% (0.9%)	-0.5% (0.6%)
Infant mortality	3.7% (1.3%)	3.1% (1.1%)	-0.6% (0.8%)
Child mortality	4.1% (1.4%)	3.4% (1.3%)	-0.7% (0.9%)
Low birth weight	17.2% (4.7%)	16.2% (4.6%)	-0.4% (4.0%)
Stunting	35.6% (8.7%)	33.2% (7.2%)	-2.4% (6.0%)
Acute Respiratory Infection (ARI)	2.5% (2.1%)	2.0% (1.3%)	-0.5% (2.2%)
Household Exposure			
Non-CF use	66.2% (27.9%)	47.8% (28.7%)	-18.4% (12.7%)
Non-CF use and no separate kitchen	26.4% (21.1%)	13.8% (13.7%)	-12.6% (11.3%)
Coal use	0.7% (4.0%)	0.8% (2.8%)	0.1% (1.6%)
Biomass use	63.6% (28.8%)	45.5% (28.5%)	-18.1% (13.3%)
Kerosene use	0.5% (1.0%)	0.2% (0.3%)	-0.3% (0.9%)
LPG use	32.0% (27.0%)	50.3% (28.4%)	18.4% (12.6%)
Household Covariates			
No smoking in the household	52.8% (18.1%)	52.8% (21.8%)	0.0% (14.5%)
Poor	18.6% (20.8%)	19.7% (20.6%)	1.1% (10.0%)
Electricity access	91.4% (13.7%)	98.2% (2.9%)	6.8% (11.9%)
Improved household sanitation	55.7% (28.9%)	80.4% (16.2%)	24.7% (18.1%)
Safe drinking water	93.5% (11.1%)	95.3% (8.3%)	1.8% (5.7%)
Literate mother	65.0% (19.9%)	63.9% (17.7%)	-1.0% (8.0%)
Mother went to college	8.7% (7.2%)	14.0% (11.0%)	5.3% (5.4%)
Underweight mother	21.6% (9.1%)	16.5% (7.8%)	-5.1% (4.9%)

Young mother	2.4% (1.5%)	2.1% (1.5%)	-0.3% (0.9%)
Household Head Caste and Religion			
Schedule Caste (SC)	15.7% (10.2%)	18.0% (11.4%)	2.3% (5.5%)
Scheduled Tribe (ST)	17.9% (30.1%)	18.1% (30.1%)	0.2% (5.3%)
Other Backward Classes (OBC)	38.1% (23.4%)	37.2% (22.8%)	-1.0% (9.2%)
Muslim	8.1% (18.0%)	7.9% (18.1%)	-0.2% (3.9%)
Ambient $PM_{2.5}$ ($\mu g/m^3$)	52 (26)	51 (25)	1 (2)
Heat Stress Index	0.07 (0.18)	0.21 (0.27)	0.15 (0.29)
Enhanced Vegetation Index (EVI)	0.29 (0.07)	0.30 (0.07)	0.00 (0.01)
Drought Index (PDSI)	0.49 (1.59)	0.41 (1.17)	-0.08 (1.40)

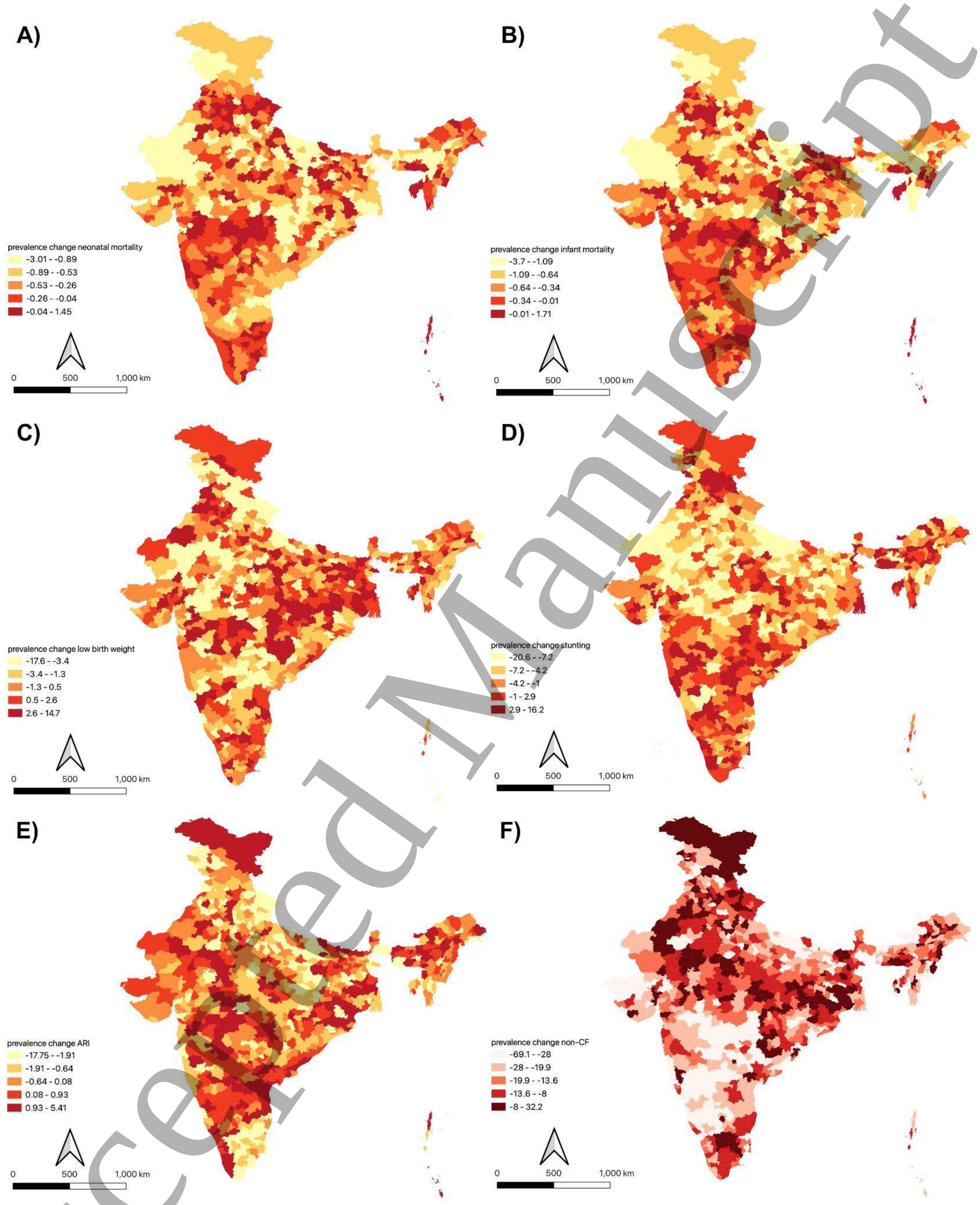

Figure 1: *Change in the prevalence (unit: percentage points) of A) Neonatal Mortality, B) Infant Mortality, C) Low Birth Weight, D) Stunting, E) Acute Respiratory Infection (ARI), and F) Non-Clean Fuel Use between the two time periods (2016-2021), classified into quantiles. Lighter yellow in panels A–E and lighter red in panel F correspond to greater decreases in prevalence.*

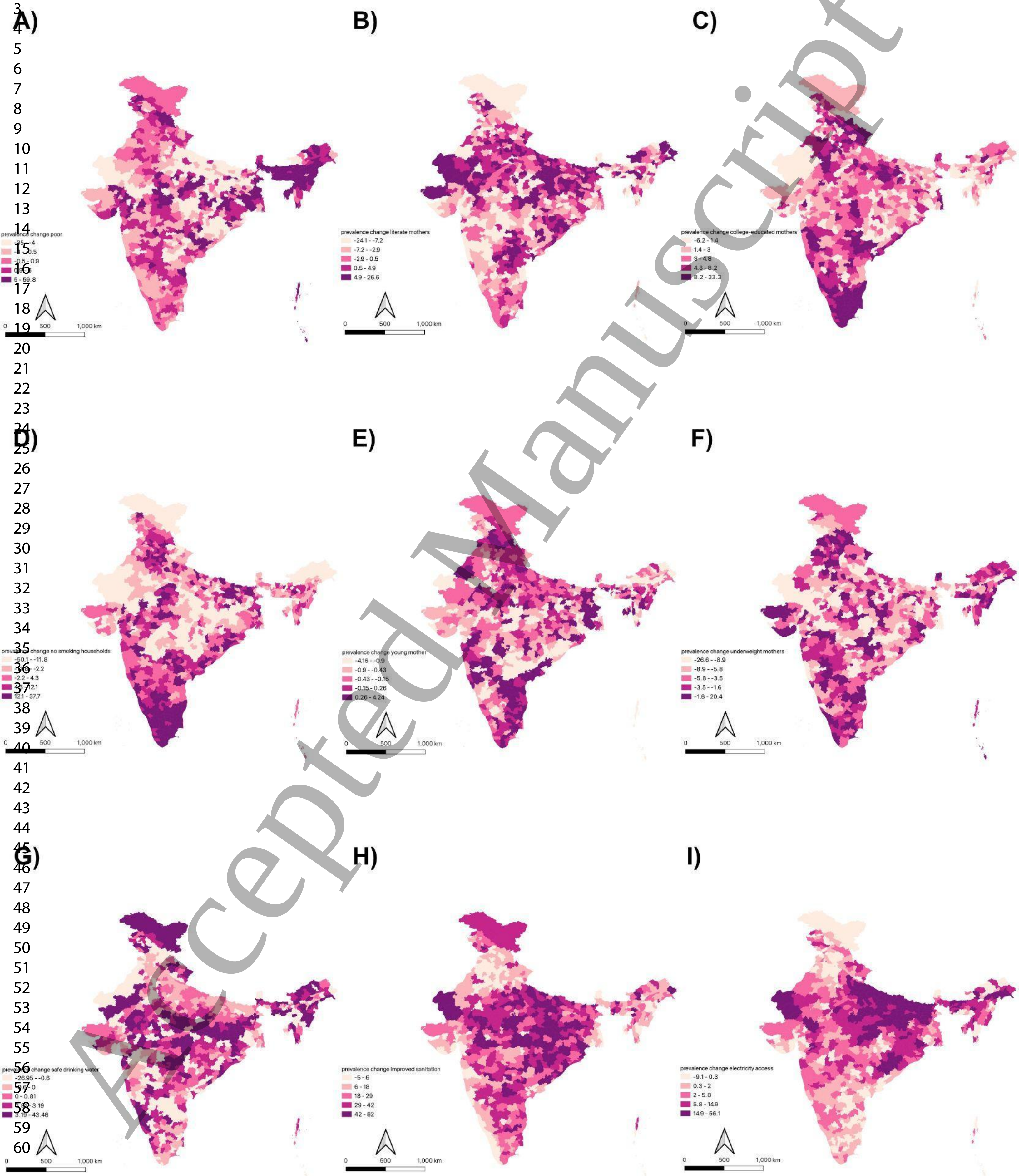
A)
prevalence change poor
-0.5 - 0.9
5 - 59.8
0
500
1,000 km
B)
prevalence change literate mothers
-24.1 - -7.2
-7.2 - -2.9
-2.9 - 0.5
0.5 - 4.9
4.9 - 26.6
0
500
1,000 km
C)
prevalence change college-educated mothers
1.4 - 3
4.8 - 8.2
8.2 - 33.3
0
500
1,000 km
D)
change no smoking households
-50.1 - -11.8
-2.2 - 4.3
12.1 - 37.7
0
500
1,000 km
E)
prevalence change young mother
-4.16 - -0.9
-0.9 - -0.43
-0.43 - -0.15
-0.15 - 0.26
0.26 - 4.24
0
500
1,000 km
F)
prevalence change underweight mothers
-26.6 - -8.9
-8.9 - -5.8
-5.8 - -3.5
-3.5 - -1.6
-1.6 - 20.4
0
500
1,000 km
G)
change safe drinking water
-26.95 - -0.6
0 - 0.81
0
500
1,000 km
H)
prevalence change improved sanitation
-5 - 6
6 - 18
18 - 29
29 - 42
42 - 82
0
500
1,000 km
I)
prevalence change electricity access
-9.1 - 0.3
0.3 - 2
2 - 5.8
5.8 - 14.9
14.9 - 56.1
0
500
1,000 km

Figure 2: *Difference between the prevalence (unit: percentage points) of A) poor households, B) literate mothers, C) college-educated mothers, D) non-smoking households, E) young mothers (< 18 yrs), F) underweight mothers, G) households with safe drinking water, H) households with improved sanitation, I) households with access to electricity between 2016-2021. The greater the decrease in the prevalence, the lighter the purple.*

3.2 District-Level Regression Results

Table 2 presents estimated associations between district-level differences in non-clean fuel (non-CF) use (primary exposure), supplementary exposures, and differences in child health outcomes. For clarity, results are presented in terms of a 10-percentage-point higher prevalence of non-CF use; because the models are linear, equivalent interpretations apply in the opposite direction (i.e., lower non-CF use corresponds to lower prevalence of outcomes when associations are positive).

In fully adjusted, population-weighted models, a 10-percentage-point higher prevalence of non-CF use was associated with a 0.70 percentage-point higher prevalence of stunting (95% CI: 0.22, 1.18). For neonatal mortality, infant mortality, low birth weight, and ARI, estimated differences were generally small, with confidence intervals spanning zero.

For supplementary exposures, a 10-percentage-point higher prevalence of LPG use was associated with a 0.59 percentage-point lower prevalence of stunting (95% CI: -1.12, -0.06) in population-weighted models. Non-CF use among households without a separate kitchen showed little association with stunting, with estimates centered near zero. However, a 10-percentage-point higher prevalence of non-CF use without a separate kitchen was associated with a 0.34 percentage-point higher prevalence of low birth weight (95% CI: 0.02, 0.66). Across outcomes, population-weighted models generally yielded larger-magnitude estimates than unweighted models.

Sensitivity analyses (**Table S3**) indicated that estimates were responsive to model specification. Inclusion of region fixed effects increased the magnitude of estimated associations, whereas additional adjustment for socioeconomic and environmental covariates attenuated estimates, consistent with confounding by regional and contextual factors.

Fully adjusted associations for all covariates are presented in **Table S4**. Differences in environmental conditions, including drought (PDSI), heat stress, and ambient $PM_{2.5}$, were consistently associated with variation in multiple outcomes, highlighting the importance of concurrent environmental exposures.

Stratified analyses by poverty status (**Table S5**) showed that among BPL households, a 10-percentage-point higher prevalence of non-CF use was associated with little difference in stunting prevalence, with estimates close to zero and wide confidence intervals. In contrast, among non-BPL households, a 10-percentage-point higher prevalence of non-CF use was associated with a 0.47 percentage-point higher prevalence of stunting (95% CI: 0.05, 0.88), indicating larger magnitude associations in this group.

Table 2*: Associations between a 10-percentage-point (pp) increase in a) non-CF use, b) non-CF use & no separate kitchen, and c) LPG use and the pp change in prevalence of child health outcomes at the district-level between 2021 and 2016 in fully-adjusted models with and without population weights^.*

	Δ Neonatal mortality	Δ Infant mortality	Δ Low birth weight	Δ Stunting	Δ Acute Respiratory Infection
	Fully adjusted model				
Main Exposure					
Δ Non-CF use (std error clustered by state)	0.02 pp (-0.03, 0.07)	0.02 pp (-0.04, 0.09)	0.07 pp (-0.18, 0.33)	0.40 pp (-0.12, 0.92)	-0.06 pp (-0.23, 0.12)
Δ Non-CF use (population^-weighted; std errors clustered by state)	0.02 pp (-0.06, 0.11)	0.04 pp (-0.06, 0.14)	0.16 pp (-0.17, 0.49)	0.70 pp (0.22, 1.18)	-0.05 pp (-0.20, 0.09)
Supplementary Exposures					
Δ Non-CF use, No separate kitchen (std error clustered by state)	0.00 pp (-0.07 , 0.07)	0.03 pp (-0.10, 0.15)	0.18 pp (-0.15, 0.51)	0.63 pp (0.08, 1.17)	0.05 pp (-0.26, 0.35)
Δ Non-CF use, No separate kitchen (population^-weighted; std errors clustered by state)	0.06 pp (-0.02, 0.14)	0.05 pp (-0.08, 0.19)	0.34 pp (0.02, 0.66)	0.31 pp (-0.32, 0.95)	-0.04 pp (-0.33, 0.25)
Δ LPG use (std error clustered by state)	-0.03 pp (-0.09, 0.03)	-0.04 pp (-0.11, 0.03)	-0.15 pp (-0.39, 0.08)	-0.30 pp (-0.85, 0.26)	0.06 pp (-0.12, 0.24)
Δ LPG use (population^-weighted; std errors clustered by state)	-0.03 pp (-0.11, 0.05)	-0.05 pp (-0.16, 0.05)	-0.17 pp (-0.48, 0.14)	-0.59 pp (-1.12, -0.06)	0.03 pp (-0.11, 0.17)

^Populations were derived by aggregating population counts for girls and boys between the ages 0-1 yr and 1-5 yrs, respectively to the NFHS-5 district level, using age- and sex-specific population data from The Gridded Population of the World, Version 4 (GPWv4) Basic Demographic Characteristics, Revision 11 for the year 2015 at a ~ 100 m resolution for India.

3.3 Individual-Level Regression Results

We first examined associations between household use of non-clean fuels and child health outcomes using pooled individual-level data from NFHS-4 and NFHS-5 (**Tables S6-S7**). In fully adjusted models, non-CF use was associated with higher odds of several adverse outcomes, including neonatal mortality (OR = 1.12, 95% CI: 1.08, 1.19), infant mortality (OR = 1.15, 95% CI: 1.09, 1.21), low birth weight (OR = 1.06, 95% CI: 1.02, 1.09), and stunting (OR = 1.17, 95% CI: 1.14, 1.19).

We then estimated difference-in-differences models restricted to BPL households (**Table 3**). Estimated differences in neonatal mortality, infant mortality, low birth weight, stunting, and ARI associated with LPG use were generally small, with confidence intervals spanning the null. Results were similar when applying propensity-score-weighted DiD models (**Table S8**).

In region-stratified analyses, associations between LPG use and child health outcomes were generally small across most regions. However, in the North-East and East, LPG use was associated with higher odds of stunting (**Table 3**), indicating regional heterogeneity in the direction and magnitude of associations. For other regions and outcomes, estimates were imprecise and centered near the null. When analyses were restricted to households without a separate kitchen, estimates similarly remained close to the null across all outcomes (**Table 3**).

Table 3*: Effect of LPG adoption among BPL households on child health outcomes. OR (95% CI) are presented with standard errors clustered at the state-level. We present results by region. We also present results specifically for BPL households with no separate kitchens.*

	Neonatal mortality	Infant mortality	Low birth weight	Stunting	Acute Respiratory Infection (ARI)
	BPL Households				
Treatment group (TRT)	0.90 (0.79, 1.02)	0.91 (0.82, 1.01)	0.97 (0.89, 1.05)	0.86 (0.81, 0.92)	1.01 (0.89, 1.13)
Post Period (POST)	0.90 (0.80, 1.02)	0.92 (0.85, 1.00)	1.05 (0.95, 1.17)	0.87 (0.77, 0.99)	0.79 (0.57, 1.11)
DiD interaction (TRT x POST)	**1.05 (0.91, 1.22)**	**1.05 (0.92, 1.20)**	**0.98 (0.88, 1.09)**	**1.05 (0.98, 1.13)**	**0.88 (0.83, 1.17)**
DiD interaction (TRT x POST)	BPL households by region				
South	**1.09 (0.60, 2.00)**	**1.20 (0.82, 1.78)**	**0.92 (0.81, 1.05)**	**0.97 (0.90, 1.06)**	**0.81 (0.60, 1.11)**
Central	**0.93 (0.79, 1.10)**	**0.90 (0.76, 1.06)**	**1.01 (0.90, 1.13)**	**0.96 (0.90, 1.03)**	**1.14 (0.97, 1.33)**
Northeast	**0.98 (0.74, 1.29)**	**0.78 (0.54, 1.14)**	**0.93 (0.76, 1.14)**	**1.18 (0.96, 1.46)**	**0.81 (0.57, 1.16)**
East	**1.04 (0.76, 1.44)**	**1.18 (0.85, 1.63)**	**0.99 (0.95, 1.03)**	**1.20 (1.15, 1.25)**	**0.86 (0.71, 1.03)**
North	**1.43 (0.98, 2.10)**	**1.26 (0.99, 1.60)**	**1.12 (0.82, 1.53)**	**1.14 (0.99, 1.32)**	**1.36 (0.94, 1.97)**
West	**1.59 (0.94, 2.71)**	**1.58 (1.02, 2.45)**	**1.10 (0.97, 1.25)**	**1.02 (0.95, 1.10)**	**0.61 (0.44, 0.85)**
	BPL households (Homes with no separate kitchens + food cooked indoors)				
Treatment group (TRT)	0.91 (0.75, 1.10)	1.01 (0.86, 1.20)	0.99 (0.87, 1.13)	0.89 (0.81, 0.97)	0.96 (0.71, 1.28)

Post Period (POST)	0.91 (0.81, 1.03)	0.90 (0.84, 0.97)	1.05 (0.93, 1.17)	0.88 (0.74, 1.06)	0.66 (0.49, 0.88)
DiD interaction (TRT x POST)	**1.15 (0.87, 1.51)**	**1.01 (0.77, 1.31)**	**0.90 (0.76, 1.07)**	**1.00 (0.91, 1.10)**	**1.10 (0.87, 1.39)**

4 Discussion

We evaluated associations between changes in district-level non-clean fuel (non-CF) use, shaped by India's clean energy policies, and changes in child health outcomes. Overall, a 10-percentage-point higher prevalence of non-CF use corresponded to a 0.70 percentage-point higher prevalence of stunting (95% CI: 0.22, 1.18). Estimates for neonatal mortality, infant mortality, low birth weight, and ARI were generally small, with confidence intervals spanning zero. In supplementary analyses, higher LPG prevalence corresponded to lower stunting prevalence, while higher non-CF use among households without a separate kitchen corresponded to higher low birth weight prevalence. These patterns were most apparent among households above the poverty line, whereas estimates among BPL households were generally centered closer to the null.

For consistency, associations are interpreted in terms of higher prevalence of non-clean fuel use; because models are linear, equivalent interpretations apply in the opposite direction (i.e., lower non-clean fuel use corresponds to lower prevalence of outcomes when associations are positive).

Although the estimated magnitude of association for stunting may appear modest, its public health significance is substantial at the population level. Given the large number of children under five in India, even small shifts in prevalence correspond to a large absolute number of affected children. Stunting is strongly associated with impaired cognitive development, reduced educational attainment, and long-term economic productivity, as well as increased risk of chronic disease later in life. Accordingly, modest improvements in stunting prevalence at the population level may yield meaningful gains in human capital and long-term health.

Importantly, the clearest patterns emerged in district-level (ecological) analyses, whereas individual-level quasi-experimental DiD models yielded estimates that were generally small and imprecise. These findings should therefore be interpreted as population-level associations rather than definitive causal effects. The divergence between ecological and individual-level results suggests that district-level patterns may reflect broader, concurrent changes in socioeconomic conditions, environmental exposures, or health systems, rather than the direct effect of household fuel transitions alone.

Our district-level analyses use linear first-difference models to estimate associations between changes in prevalence, an estimand defined on the absolute (percentage-point) scale that is directly interpretable for policy evaluation. Because the outcome is a continuous change in modeled prevalence, which can take negative values, binomial likelihoods are not applicable.

Alternative approaches, such as inverse-variance-weighted regression using first-stage precision estimates or joint hierarchical Bayesian models, could improve efficiency by more fully accounting for heteroskedasticity and propagating uncertainty from the prevalence-estimation stage. Our approach partially addresses these issues through population weighting and clustered standard errors but does not fully propagate first-stage uncertainty; accordingly, estimates may be conservative.

The ecological design further limits causal interpretation. First-difference models assume that unobserved confounders are time-invariant or evolve smoothly over time such that differencing removes their influence. While this assumption is plausible over the five-year interval between NFHS-4 and NFHS-5, it may be violated by abrupt, district-specific changes in policies, economic conditions, or health systems. These models also assume linear and additive relationships between changes in fuel use and changes in health outcomes; however, true relationships may be non-linear or involve threshold effects. In addition, district-level analyses assume that changes in aggregate fuel use proxy changes in individual exposure, an assumption that may be weakened by heterogeneity in adoption and fuel stacking. Finally, district-level prevalences were derived from multilevel models and incorporate estimation uncertainty that is not explicitly carried into the second stage. As a result, associations may reflect correlated area-level changes rather than individual-level exposure–response relationships. Nevertheless, such analyses remain informative for population monitoring and for identifying broad spatial patterns.

At the individual level, we observed strong cross-sectional associations between non-CF use and several adverse outcomes. However, DiD estimates of changes following LPG adoption were generally small and imprecise, including among BPL households targeted by PMUY, consistent with prior randomized and quasi-experimental studies reporting limited or null health improvements (Checkley et al., 2024; Raheel et al., 2025; Simkovich et al., 2020; Younger et al., 2024). These models rely on a parallel trends assumption—that outcomes among adopters and non-adopters would have evolved similarly in the absence of LPG adoption—which cannot be directly tested in this setting and may be violated if adopting households differ in unobserved ways. Together, these findings suggest that increased access to LPG may not have translated into sufficiently large or sustained reductions in household air pollution exposure to produce measurable health improvements over the study period.

The poverty-stratified findings are particularly noteworthy. Although PMUY primarily targeted BPL households, estimated associations were more pronounced among non-BPL households. One explanation is that LPG adoption among poorer households may not have resulted in comparable reductions in exposure due to continued fuel stacking driven by refill costs, supply constraints, and cooking practices. By contrast, non-BPL households may have been better positioned to adopt LPG more consistently and exclusively, such that changes in reported fuel use more closely reflect meaningful exposure reductions.

A second, non-mutually exclusive explanation is that health gains from cleaner cooking may be more difficult to detect among poorer households because child health is shaped by multiple overlapping risks, including undernutrition, poor sanitation, infection burden, and limited access to healthcare. In such contexts, reductions in household air pollution may have smaller or less detectable marginal effects.

Several additional factors may explain these findings. First, NFHS-5 was conducted during the COVID-19 pandemic, a period of substantial social and economic disruption. Changes in time use, cooking behavior, and fuel access may have increased fuel stacking and weakened the correspondence between reported primary fuel type and actual exposure. If primary fuel status became a noisier proxy for exposure, estimated associations, particularly in individual-level analyses, would be biased toward the null. Pandemic-related shocks may also have independently affected child health outcomes.

Second, our exposure measure captures only the primary cooking fuel, whereas fuel stacking remains widespread. Households classified as LPG users may therefore continue to rely on polluting fuels, leading to exposure misclassification. More broadly, fuel type is an imperfect proxy for indoor air pollution: differences in stove technology, kitchen location, ventilation, and housing conditions mean that equivalent changes in fuel use may not translate into comparable exposure reductions. These factors likely attenuate true exposure-response relationships.

Finally, some outcomes are subject to measurement error. Anthropometric measures used to define stunting are generally reliable, although random error may attenuate associations. In contrast, ARI is based on maternal report and may be misclassified, and birth weight is not universally recorded and may rely on recall. Such misclassification is likely non-differential and would bias estimates toward the null.

Several covariates are also self-reported and may be measured with error, contributing to residual confounding and attenuation of estimated associations. Together, these sources of exposure, outcome, and covariate misclassification suggest that the absence of clear signals in quasi-experimental analyses may reflect attenuation of underlying associations rather than their absence. At the same time, aggregation to the district level introduces additional uncertainty, and residual confounding may bias estimates in either direction.

Consistent with this interpretation, increases in access to clean fuels may have coincided with improvements in population-level indicators without generating sufficiently large or sustained reductions in individual exposure to affect health outcomes over the study period. This pattern aligns with prior evidence that access does not necessarily translate into exclusive use or meaningful exposure reduction.

These findings have implications beyond India. Similar patterns have been observed in other low- and middle-income countries undergoing transitions to cleaner household energy. Randomized and quasi-experimental studies in settings including Peru, Ghana, and Rwanda have documented substantial reductions in pollutant concentrations but limited or inconsistent improvements in health outcomes, particularly for outcomes such as child growth and birth weight. This broader evidence suggests that increasing access to clean fuels alone may be insufficient to produce measurable health gains without sustained, exclusive use and meaningful reductions in exposure. Structural constraints, including affordability, fuel supply reliability, cultural cooking practices, and housing conditions, may limit the extent to which cleaner fuels displace traditional fuels across diverse contexts.

More broadly, these results highlight a central challenge in translating environmental interventions into health gains: exposure reductions must be sufficiently large, sustained, and occur during critical developmental windows to influence outcomes such as stunting. Policies focused primarily on access may therefore underestimate the importance of behavioral, infrastructural, and economic factors that shape real-world exposure. Integrating exposure monitoring, affordability interventions, and improvements in housing and ventilation may be necessary to achieve meaningful and equitable health benefits.

Important research gaps remain. National surveys lack direct measurements of household air pollution, personal exposure, stove usage patterns, and fuel stacking behavior, limiting the ability to link policy-driven transitions to realized exposure reductions and health outcomes. Longitudinal household panels integrating exposure monitoring and behavioral data are needed to disentangle adoption from sustained use and to assess longer-term effects. Future work should also examine heterogeneity by housing conditions, baseline pollution, supply reliability, and interactions with ambient air pollution and climate stressors.

Despite these limitations, this study provides a scalable framework for evaluating large-scale clean energy transitions using repeated nationally representative data. The findings highlight that expanding access alone may be insufficient to achieve measurable health gains, underscoring the need for policies that support sustained, exclusive use and meaningful exposure reduction.

Author Contributions

PD conceptualized the analysis, developed the methodology, wrote the first draft, and revised and edited the draft. All authors contributed to the methodological development and revised and edited the draft.

Declaration of Interests

The authors declare no competing interests.

Data Availability Statement

NFHS data is available on submitting a request via the DHS website https://dhsprogram.com/. The $PM_{2.5}$ data are freely available from https://sites.wustl.edu/acag/datasets/surface-pm2-5/. Data on all other environmental exposures were obtained from Google Earth Engine.

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