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Impact of Pradhan Mantri Ujjwala Yojana (PMUY) On Child Health and Clean Fuel Adoption in India: A State-Level Difference-In-Differences Analysis

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ABSTRACT

This study is situated in Development Economics with strong links to Health Economics, evaluating whether a poverty-targeted public policy in India improved household welfare through cleaner energy adoption and child health outcomes. The research evolved from a broad inquiry into whether the Pradhan Mantri Ujjwala Yojana (PMUY), India's large-scale LPG subsidy program launched in 2016, reduced child Acute Respiratory Infection (ARI) prevalence and increased household clean fuel use, to a more focused examination of whether states with higher implementation intensity experienced greater improvements. Using a state-level panel from NFHS-4 (2015–16) and NFHS-5 (2019–21), the study applies a Difference-in-Differences framework with state fixed effects and time-varying controls. PMUY exposure is measured using binary high-versus-low implementation indicators and continuous intensity variables. Findings suggest higher PMUY intensity is associated with modest additional declines in child ARI prevalence in binary specifications, though this effect is statistically fragile and not robust in continuous models. Clean fuel adoption rose substantially across states, but PMUY intensity variation explains only a limited share of this increase. Results indicate that while PMUY may have contributed to limited health gains, connection provision alone is insufficient without sustained, affordable LPG use.

INTRODUCTION

Indoor air pollution from biomass fuel combustion represents a critical public health challenge in South Asia, contributing approximately 3.8 million premature deaths globally with disproportionate impacts on women and children in low-income households [1]. India bears nearly one-quarter of the global disease burden from household air pollution, with children under age five experiencing acute Respiratory Infection rates twice as high in biomass-using households compared to clean fuel users[2]. The Pradhan Mantri Ujjwala Yojana (PMUY), launched in May 2016, represents an unprecedented scale of LPG expansion, providing free connections to 50 million Below Poverty Line households by 2019[3].

This research is situated primarily in Development Economics, with strong connections to Health Economics and Environmental Economics, because it evaluates a poverty-targeted public intervention and examines its effects on household welfare, energy adoption and child health outcomes. The study began as a broad causal question about whether PMUY reduced child ARI and increased clean fuel use. As the project matured, the focus shifted to a more operationalised empirical inquiry: **Whether states with higher PMUY implementation intensity achieved greater reductions in child ARI prevalence and larger gains in clean fuel adoption than lower-intensity states between NFHS-4 and NFHS-5, and whether such effects were robust across alternative treatment specifications**.

Despite PMUY's scale, rigorous evidence on program effectiveness in improving health outcomes remains limited. Existing studies document substantial implementation variation across states and concerning patterns of incomplete fuel transitions despite connection access [4][5]. This study addresses this evidence gap by implementing a state-level Difference-in-Differences approach to provide policy-relevant evidence on whether large-scale energy access interventions successfully translate connection provision into behavioural change and health improvements.

The remainder of this paper is organised as follows: Section 2 reviews relevant literature; Section 3 describes data and sources; Section 4 outlines the methodology and identification strategy; Section 5 presents empirical results; Section 6 discusses findings, policy implications and limitations; and Section 7 concludes.

LITERATURE REVIEW

Household Air Pollution and Child Health

Household air pollution from solid fuel combustion is a well-documented risk factor for acute respiratory infections in children under five years of age [6]. Exposure to indoor particulate matter and carbon monoxide from biomass burning damages the respiratory epithelium and impairs immune response, increasing susceptibility to pneumonia and bronchiolitis [7]. Cross-sectional studies in India consistently show two- to three-fold higher ARI prevalence in households using traditional biomass cookstoves compared to LPG users. However, most evidence is observational, with limited quasi-experimental or experimental designs capable of establishing causal effects of fuel transitions on child health outcomes.

Clean Fuel Transitions and Fuel Stacking

Research on LPG adoption in developing countries reveals persistent fuel stacking behaviour, where households continue using traditional fuels alongside LPG rather than switching completely [8][9]. Affordability constraints on LPG refills, cultural cooking preferences and spatial segregation of cooking tasks contribute to incomplete transitions [10]. Studies of PMUY beneficiaries in India document that while connection ownership increased dramatically, refill rates remained low, with many households reverting to biomass for regular cooking [11]. This suggests that measuring "main cooking fuel" at the household level may overstate actual clean fuel use intensity, limiting the health benefits captured in aggregate data.

PMUY and Policy Evaluation Evidence

Early evaluations of PMUY show mixed results. Administrative data confirm massive expansion in LPG connections, particularly in rural and economically disadvantaged states. However, studies using household survey data find that PMUY connections alone do not guarantee sustained LPG use or elimination of solid fuel consumption [12]. Health impact evaluations remain scarce, with most focusing on self-reported respiratory symptoms rather than clinically validated outcomes [13]. State-level heterogeneity in implementation quality, refill subsidy delivery and complementary infrastructure investment suggests that program intensity may matter more than simple connection counts.

Research Gap

This study contributes to the literature by employing a state-level Difference-in-Differences design to estimate whether variation in PMUY implementation intensity is associated with differential changes in child ARI prevalence and clean fuel adoption between two nationally representative health surveys. This analysis examines clinically relevant child health outcomes while accounting for state fixed effects, time-varying covariates and alternative treatment specifications to test the robustness of findings.

Data and Data Source

Dataset Construction

The analysis employs a manually assembled state-level panel dataset combining published National Family Health Survey (NFHS) fact sheets with administrative policy data. State-level outcome data are drawn from NFHS-4 (2015–16) and NFHS-5 (2019–21) India reports and factsheets for 36 states and union territories, yielding 72 state-period observations. After excluding units with missing PMUY information, 64–67 observations are usable in regression models, depending on the specification.

The two primary outcomes are: (1) **Child ARI prevalence**, measured as the percentage of under-five children with ARI symptoms in the two weeks preceding the survey; and (2) **Household clean fuel use**, measured as the percentage of households using LPG, electricity, biogas or piped gas as their main cooking fuel. At the national level, clean fuel use increased from approximately 50 per cent to 64 per cent between NFHS-4 and NFHS-5, while child ARI prevalence remained relatively stable at around 2.3–2.4 per cent.

PMUY implementation intensity is quantified using cumulative PMUY LPG connections by state up to 2019, as reported in administrative records from the Ministry of Petroleum and Natural Gas. In the baseline specification, states with cumulative connections at or above the 2019 median (approximately 352,921 connections) are classified as "high-PMUY," while those below are designated as "low-PMUY." A continuous dose-response measure is also constructed using the number of PMUY connections directly, allowing intensity to be modelled as a linear variable.

Time-varying state-level controls include women's literacy, women's tobacco use and household electricity access from NFHS. These variables control for evolving socioeconomic and infrastructural conditions correlated with both PMUY rollout and health outcomes.

Data Acquisition and Software

Data for the study were compiled from NFHS-4 and NFHS-5 state fact sheets and administrative PMUY records to construct a two-period state-level panel. The empirical analysis was conducted in Stata, which was used for data structuring, panel setup using xtset, descriptive statistics and fixed-effects Difference-in-Differences estimation with clustered standard errors at the state level.

Descriptive Statistics

The dataset comprises 72 state-period observations with substantial variation across outcomes and covariates. Clean fuel use averages 57.14 per cent across observations, with variation from 17.8 per cent to 98.94 percent, whereas child ARI prevalence averages 2.34 percent and ranges from 0.3 percent to 5.8 percent. Women's literacy averages 77.88 per cent and electricity access 95.80 per cent, indicating generally high but uneven social and infrastructure conditions across states. PMUY connections are available for 64 observations and display very large dispersion, with a mean of approximately 2.08 million, a minimum of 88 and a maximum of 12.96 million connections. These descriptive patterns support the use of a panel Difference-in-Differences design, as they reveal both cross-state heterogeneity and meaningful variation in policy intensity and outcome variables of interest. Detailed descriptive statistics are presented in Table 1.

METHODOLOGY

Panel Setup and Treatment Definition

The dataset is structured as a two-period panel with states as units. State names are encoded as numeric identifiers, and the panel is declared with **xtset state_id** Post, where Post = 0 for NFHS-4 (2015–16) and Post = 1 for NFHS-5 (2019–21). PMUY connections are made time-invariant within states by using each state's cumulative connections as of 2019.

Binary treatment indicator: $\boldsymbol{HighPMUY_s = 1}$ if cumulative PMUY connections in 2019 are at or above the median cutoff (352,921 connections), and 0 otherwise.

The corresponding Difference-in-Differences term is the interaction $\boldsymbol{HighPMUY_s} \times \boldsymbol{Post_t}$.

Continuous intensity measure: $\boldsymbol{PMUYIntensity_s = PMUY\_2019_s}$, with interaction $\boldsymbol{PMUYIntensity_s} \times \boldsymbol{Post_t}$, allowing a linear dose-response test of the effect of PMUY intensity on outcomes.

Baseline Difference-in-Differences Specification

For state s and period t, the baseline binary-treatment DiD model is:

$$\boldsymbol{Y_{st} = \alpha_s + \gamma Post_t + \beta(HighPMUY_s \times Post_t) + X'_{st}\delta + \varepsilon_{st}}$$

where Y_{st} is either child ARI prevalence or clean fuel use, $HighPMUY_s$ is the high-PMUY indicator, $Post_t$ is a post-period dummy (NFHS-5), X_{st} is the vector of controls (women's literacy, women's tobacco use, electricity access), and α_s are state fixed effects. The coefficient β captures the average DiD effect of being a high-PMUY state in the post period. Estimation uses fixed-effects regressions with state-level clustered standard errors.

Continuous Dose-Response Specification

To avoid information loss from dichotomising PMUY and to better exploit cross-state variation, a continuous-intensity DiD model is estimated:

$$\boldsymbol{Y_{st} = \alpha_s + \gamma Post_t + \beta(PMUYIntensity_s \times Post_t) + X'_{st}\delta + \varepsilon_{st}}$$

where $PMUYIntensity_s$ denotes state-level PMUY connections. The coefficient β measures how within-state changes in Y_{st} differ as PMUY intensity increases in the post period.

Identification Strategy

The main specification uses a two-period state-level Difference-in-Differences framework with state fixed effects and a post-period indicator to estimate whether outcomes changed differentially in states with greater PMUY exposure between NFHS-4 and NFHS-5. PMUY exposure is defined in two ways: first, as a binary indicator for high-PMUY states based on the median 2019 cumulative PMUY connections; second, as a continuous treatment intensity measure using state-level PMUY connections.

Identification relies on a **conditional parallel-trends assumption**: absent differential PMUY intensity, high- and low-PMUY states would have experienced similar changes in outcomes over time after accounting for state fixed effects, the common post-period effect, and observed time-varying covariates. State fixed effects absorb all time-invariant differences across states, such as long-run infrastructure, geography, and persistent cultural or institutional factors, while the post dummy captures common national shocks affecting all states.

The main specification includes only **time-varying controls** such as women's literacy, women's tobacco use and electricity access. This is important because, in a fixed-effects framework with only two periods, purely baseline state characteristics and baseline outcome levels are time-invariant and are therefore absorbed by the state fixed effects. As a result, they do not provide additional identifying variation in the principal fixed-effects specification.

Endogeneity is mitigated by state fixed effects, which absorb time-invariant state characteristics; a post dummy, which captures common national shocks between NFHS-4 and NFHS-5; and time-varying covariates, which control for evolving socioeconomic and infrastructural conditions correlated with both PMUY rollout and outcomes. Nonetheless, unobserved time-varying state-level policies or governance changes that coincide with PMUY implementation may introduce bias into the estimates. Given that only two NFHS rounds are available, the parallel-trends assumption cannot be tested directly using pre-treatment trends. Accordingly, the estimated coefficients should be interpreted as policy-relevant associations consistent with the DiD design, rather than definitive causal effects.

A standardised balance check on baseline covariates shows that high-PMUY states are, on average, more disadvantaged at baseline (higher ARI, lower clean fuel use, lower literacy, and lower electrification), justifying the use of fixed effects and careful identification assumptions.

RESULTS

Descriptive Patterns

Pre-period (NFHS-4) tabulations indicate that child ARI prevalence averages about 2.35 per cent overall, with low-PMUY states at 1.92 per cent and high-PMUY states at 2.66 per cent. High-PMUY states start with slightly higher ARI, showing their more disadvantaged baseline profiles. Clean fuel use averages 50.09 per cent overall in NFHS-4, with low-PMUY states at 54.43 per cent and high-PMUY states at 46.99 per cent. Low-PMUY states have somewhat higher baseline clean fuel adoption.

Between NFHS-4 and NFHS-5, child ARI remains broadly flat (2.35 to 2.32 per cent overall), while clean fuel use rises sharply (50.09 to 64.18 per cent overall, an increase of about 14 percentage points in the raw means). These patterns are consistent with aggregate NFHS reports.

Child ARI Results

Binary DiD Model (High vs Low PMUY): In the fixed-effects binary-treatment model for child ARI, the interaction term between high-PMUY status and the post period is approximately −0.95 percentage points (robust SE ≈ 0.47, $p = 0.049$, 95% CI [−1.91, −0.00]). This implies that high-PMUY states underwent approximately a one-percentage-point larger decline in under-five ARI prevalence between NFHS-4 and NFHS-5 than low-PMUY states, conditional on controls and state/time effects. Given national ARI levels of roughly 2–3 per cent, this effect is epidemiologically meaningful (representing roughly a 40% relative reduction from baseline ARI in high-PMUY states) but only marginally statistically significant, with relatively wide confidence intervals and a p-value just at the conventional 5% threshold.

The post dummy in this model is about −0.58 percentage points ($p \approx 0.22$), indicating little common national change in ARI after controlling for covariates, consistent with ARI remaining roughly flat in the descriptive statistics.

Continuous-Intensity Models: The continuous-intensity specifications for child ARI, using PMUY connections as a linear dose, yield a coefficient on the interaction term of approximately -9.2×10^{-8} ($p \approx 0.24$). Interpreted literally, this suggests a very small negative association between additional PMUY connections and ARI changes in the post period (for 1 million more connections, ARI change ≈ −0.09 percentage points), but this estimate is not statistically significant. The continuous models thus confirm the direction suggested by the binary DiD but do not reveal a strong, statistically precise linear dose-response relationship. This is consistent with the interpretation that the binary high/low split captures most of the interpretable variation and that measurement noise, nonlinearity, or unmeasured factors limit the power of a linear intensity specification.

Clean Fuel Adoption Results

Binary DiD Model (High vs Low PMUY): In the clean-fuel regressions, the post dummy is large and highly statistically significant, with a coefficient of approximately +16.6 percentage points ($p < 0.001$), signifying a strong nationwide increase in clean fuel use between NFHS-4 and NFHS-5, in line with NFHS summaries. The within R^2 of the clean-fuel model is high (around 0.87 in the binary specification), showing that the combination of post effects, fixed effects and controls explains much of the within-state variation in clean fuel adoption over time.

By contrast, the DiD interaction term between high-PMUY status and the post period is small (about −0.44 percentage points) and extremely imprecise ($p \approx 0.87$), with confidence intervals spanning a wide range around zero. This indicates no clear differential gain in clean fuel use between high-PMUY and low-PMUY states beyond the strong national trend.

Electricity access is positively and significantly associated with clean fuel use (coefficient ≈ 0.25, $p \approx 0.018$), consistent with wider energy infrastructure facilitating LPG uptake. Literacy and tobacco use remain statistically insignificant.

Continuous-Intensity Models: Continuous-intensity specifications similarly yield coefficients on the interaction term that are near zero and statistically insignificant (coefficient $\approx 4.5 \times 10^{-8}$, $p \approx 0.87$). These results reinforce the conclusion that, once one conditions on the large common post-trend and structural covariates, cross-state variation in PMUY intensity explains little of the national increase in clean fuel use. The high within R^2 indicates that the model explains variation well overall, but the incremental contribution of PMUY intensity over and above common national factors and state-specific baseline conditions remains negligible.

Full regression results for all four main specifications are presented in **Table 2.**

DISCUSSION, CONCLUSION, POLICY IMPLICATIONS AND LIMITATIONS

Discussion

The joint pattern—modest, borderline-significant ARI improvements in higher-intensity PMUY states and weak differential gains in clean fuel adoption across intensity levels—is consistent with external evidence on fuel stacking and constrained LPG usage among PMUY beneficiaries. Studies of LPG use in India report that many households continue to rely on solid fuels alongside LPG and that refill frequency is often low because of affordability and access constraints, limiting the health impact of nominal LPG connection ownership [14][15].

Under such conditions, state-level indicators of "main cooking fuel" do not fully capture the intensity and continuity of LPG use needed to deliver large, statistically robust reductions in child ARI at the aggregate level. The findings therefore suggest that more intensive PMUY rollout is associated with a small additional reduction in child ARI prevalence, consistent with some health benefits accruing where LPG is actually and consistently used. However, this effect is only marginally statistically significant and not robustly detected in continuous-intensity specifications, suggesting fragility and prudence in causal interpretation.

Differences in PMUY intensity account for only a limited share of the large national increase in clean fuel adoption between NFHS-4 and NFHS-5. Both binary and continuous-intensity models show that common national factors and persistent structural conditions explain much of the observed variation, with PMUY rollout intensity itself adding little incremental explanatory power beyond baseline state characteristics and nationwide trends.

Policy Implications

From a policy perspective, these findings underscore the need to move beyond connection-based coverage metrics to focus on sustained and affordable LPG use, as well as meaningful reductions in solid-fuel reliance, to achieve greater and more detectable improvements in child respiratory health. The results highlight the importance of addressing affordability, supply-chain access, and behavioural factors that influence actual cooking fuel choices and usage intensity, rather than relying solely on nominal LPG connections as an indicator of program success.

Policy interventions that combine connection provision with refill subsidies, local distribution infrastructure, behaviour change communication, and monitoring of actual fuel use may be more effective in generating sustained health benefits. Future program evaluations should measure LPG refill frequency, household fuel consumption patterns, and biomarker-based health outcomes rather than relying exclusively on self-reported main fuel status.

Limitations

This study has several important limitations. **First**, the analysis relies on only two NFHS rounds, precluding direct tests of the parallel-trends assumption or examination of dynamic treatment effects. **Second**, state-level aggregation obscures household-level heterogeneity in PMUY uptake, LPG usage intensity, and health outcomes, limiting causal inference about individual-level mechanisms. **Third**, the treatment intensity measure uses absolute PMUY connections rather than a normalised per-capita or per-household metric, which may confound state size with implementation intensity.

Fourth, child ARI is measured based on maternal recall of symptoms in the two weeks preceding the survey, introducing potential measurement error and recall bias. **Fifth**, unobserved time-varying state policies, economic shocks or complementary health interventions may confound the estimated treatment effects. **Finally,** the modest and fragile statistical significance of the ARI results, combined with the null findings for clean fuel adoption, suggest that state-level variation in PMUY intensity may be too coarse to detect health impacts if benefits are highly localised or contingent on sustained usage patterns not captured in aggregate data.

Conclusion

This study examined whether higher PMUY implementation intensity at the state level is associated with greater reductions in child ARI prevalence and larger increases in household clean fuel adoption between NFHS-4 and NFHS-5. Using a Difference-in-Differences framework with state fixed effects and time-varying controls, the analysis found modest evidence that high-PMUY states experienced small additional declines in child ARI, though this effect is statistically fragile and not robust across specifications. Clean fuel adoption increased substantially nationwide, but cross-state variation in PMUY intensity contributed little explanatory power beyond common trends and structural factors.

The findings suggest that connection-based LPG access programs like PMUY may generate limited health benefits when households face affordability constraints, supply-chain barriers, and persistent fuel stacking behaviours. Effective policy design requires attention to sustained usage, refill subsidies, and behavioural support, not just connection counts. Future research should employ household-level panel data, biomarker-based health measures, and longer time horizons to better understand the conditions under which energy access interventions translate into meaningful health gains.

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TABLES

Table 1. Descriptive Statistics

Variable	**Observations**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Clean fuel use (%)	72	57.136	22.536	17.80	98.94
Child ARI symptoms (%)	72	2.336	1.331	0.30	5.80
Women tobacco use (%)	72	12.212	14.462	0.10	61.58
Men tobacco use (%)	72	41.426	16.414	12.06	80.40
Women literacy (%)	72	77.881	10.937	49.60	98.27
Electricity access (%)	72	95.798	6.916	58.60	100.00
PMUY connections, 2019	64	2,075,200	3,075,745.5	88	12,963,097

Notes: The dataset is a two-period state-level panel with 72 state-period observations. PMUY connection data are available for 64 observations.

Table 2. Pre-Period Means by PMUY Treatment Group, NFHS-4

Outcome	**Low-PMUY States**	**High-PMUY States**	**Overall**
Child ARI prevalence (%)	1.92	2.66	2.35
Clean fuel use (%)	54.43	46.99	50.09

Notes: High-PMUY states are defined as states with cumulative PMUY connections at or above the 2019 median cutoff of 352,921. These values refer to the pre-treatment period, NFHS-4 (2015-16).

Table 3. Overall Means by Survey Round

Outcome	**NFHS-4**	**NFHS-5**	**Change**
Child ARI prevalence (%)	2.35	2.32	-0.03
Clean fuel use (%)	50.09	64.18	14.09

Notes: These are raw means across survey rounds.

Table 4. Main Difference-in-Differences Regression Results

Variable / Statistic	**Child ARI: Binary DiD**	**Child ARI: Continuous Intensity**	**Clean Fuel: Binary DiD**	**Clean Fuel: Continuous Intensity**
Post	-0.58	-0.73	16.61***	16.59***
DiD interaction	-0.95**	-9.20e-08	-0.44	4.49e-08

Robust standard error of interaction	0.47	7.63e-08	2.61	2.71e-07
p-value of interaction	0.049	0.237	0.867	0.870
95% confidence interval of interaction	[-1.906, -0.003]	[-2.47e-07, 6.33e-08]	[-5.712, 4.835]	[-5.07e-07, 5.97e-07]
Within R-squared	0.208	0.129	0.871	0.871
State fixed effects	Yes	Yes	Yes	Yes
Clustered standard errors	Yes	Yes	Yes	Yes

Notes: Columns 1 and 2 use child ARI prevalence as the dependent variable. Columns 3 and 4 use clean fuel use as the dependent variable. The binary DiD interaction is High-PMUY × Post. The continuous treatment interaction is PMUY intensity × Post. Standard errors are clustered at the state level. Significance levels: *** $p < 0.01$, ** $p < 0.05$.

Table 5. Magnitude and Interpretation of Main Effects

Model	**Estimated Effect**	**Interpretation**
Child ARI, binary DiD	-0.95 percentage points	High-PMUY states experienced a roughly 1-percentage-point larger decline in child ARI than low-PMUY states.
Child ARI, continuous intensity	-9.20e-08	An additional 1 million PMUY connections is associated with about a 0.09 percentage-point reduction in child ARI.
Clean fuel, binary Post effect	16.61 percentage points	Overall, clean fuel adoption increased sharply between NFHS-4 and NFHS-5.
Clean fuel, binary DiD	-0.44 percentage points	There is no meaningful additional clean-fuel gain in high-PMUY states relative to low-PMUY states.
Clean fuel, continuous intensity	4.49e-08	The continuous PMUY intensity effect is essentially zero.